



Accounting for the importance of psychological distance in assessing public preferences for air quality improvement policies: an application of the integrated choice and latent variable model

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Received: 4 July 2022 / Accepted: 29 January 2023 / Published online: 6 February 2023
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Abstract

Assessing public preferences for air pollution control is essential to achieving effective air quality improvement, but the internal psychological factors affecting public preferences, especially psychological distance (PD), have only received limited attention. Therefore, this paper explores the role of PD in assessing public preferences for air quality improvement policies. Compared with previous studies that consider psychological factors in the choice model, this study incorporates PD into the choice model as a latent variable by considering both individual responses to measurement questions and socio-economic characteristics in the integrated choice and latent variable model. The results of this study clearly show that PD significantly affects public preferences for air quality improvement policies. Respondents with close PD had obvious preferences for air quality improvement, while those with distant PD were satisfied with the current situation and reluctant to improve it. After considering PD in the analysis, respondents' willingness to pay for one-unit level change of attributes "heavily polluted days," "good air days," "mortality," and "policy postponement" were respectively 10.3791CNY, 10.9005CNY, 11.0427CNY, 28.3412CNY per year. In addition, the paper also found men and respondents with lower levels of education and higher monthly incomes tended to view air pollution as psychologically distant and thus less willing to improve air quality. It is suggested that policy makers should reduce the PD of air pollution among these people by increasing publicity about the hazards of air pollution. This study not only contributes to the literature on the importance of PD in assessing individual preferences, but also provides constructive guidance for policy makers to assess the public's acceptability of air quality improvement.

Keywords Air pollution · Psychological distance · Choice experiment · Latent variable · Integrated choice and latent variable model

Introduction

In recent years, China, as the biggest developing country in the world, has made progress in economy and society that has been acknowledged throughout the world. However, with the development of the economy and society, environmental issues such as air pollution (Li et al. 2018), unbalanced and unsustainable development (Cao et al. 2014) and natural resources loss (Li et al. 2004) are becoming increasingly apparent. Among them, air pollution has received a lot of attention as an environmental problem that directly affects public life. Air pollution has brought a lot of serious harm to people and society, which has become a severe problem in public lives which affects their health, work, and even mood (Dong 2019; Yin et al. 2018; Zheng et al. 2019). Therefore, there is an urgent need to take measures to enhance air quality (Zhao et al. 2020). Although the

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state and government departments have implemented many measures to solve the problem, it remains severe in many regions, particularly in northeast China, where there are many heavy industry cities and long winter heating cycles (Aunan et al. 2017). The residents who live near industrial areas have suffered from air pollution for a long time (Sun et al. 2021). It is evident that the problem of air pollution is a huge challenge for the whole society and has not been effectively controlled so far.

To improve air quality, it is not sufficient to rely only on the efforts of government departments. According to Li et al. (2018), air pollution can be effectively controlled only when the government and public work together to mitigate the problem. The public plays an irreplaceable role in the current environmental air pollution control work. However, studies have shown that individuals often attribute air pollution problems to places far away from them rather than to local communities (Bickerstaff 2004). Meanwhile, this psychological perception is regarded as an important factor affecting the willingness of individuals to participate in environmental protection (Liu et al. 2021). Therefore, it is necessary to understand the public's psychological perceptions and reactions to air pollution, which will contribute to formulating more cost-effective policies and measures for improvement.

Recently, more and more scholars have begun to focus on the public's psychological perception of air pollution, such as risk perception (Oltra and Sala 2016) and psychological distance (PD) (Cheng et al. 2021). In particular, the PD has been widely used to explain individual behavior and preferences. PD seems to be believed to play an important role in promoting environmental behavior change and willingness to pay (WTP) (Brügger 2020; Cheng et al. 2021; Mir et al. 2016; Singh et al. 2017). Therefore, testing PD in the context of air pollution can help to understand the individual attitudes towards air quality improvement and acceptability of policies, thereby timely revealing potential sources of conflict. However, few scholars have further transformed PD into an influencing variable to explore its impact on air quality improvement policy preferences.

The choice experiment (CE) method is employed to provide hypothetical scenarios with multiple attributes for respondents, which has been widely used to reveal the public's preferences and evaluate the implicit value of non-market goods (Andreopoulos et al. 2015; Khan et al. 2019). In the CE method, the main attributes and levels of a particular good or service are first identified, and then they are combined into many different alternatives. Finally, respondents are asked to select their most preferred alternative from a sequence of choice tasks. Some previous studies have investigated the public's preferences and WTP for air quality improvement policies using CE (Tang

and Zhang 2015; Yoo et al. 2008). While these studies have confirmed public support for air quality improvement policies, the source of their motivation remains unclear.

This study will help scholars realize the PD can be regarded as an important factor affecting individual choice preferences for air quality improvement policies. PD is firstly employed in an integrated choice and latent variable (ICLV) model, which has been proved to reasonably explain the influence of psychological factors on public preferences in various research areas (Aaditya and Rahul 2021; Jing et al. 2020; Mohammadi et al. 2021). It is worth noting that the ICLV model allows a simultaneous estimation across the PD measurement data, socio-economic characteristics (e.g., gender and income) and individual choice preferences for air quality policies. This is of great concern because any sequential estimation that considers latent variables in the choice model causes the problem of bias in parameter estimators (Hoyos et al. 2015).

The main purpose of this study is (1) to explore the public's preferences and WTP for multi-attribute air quality improvement policies, and (2) under this background, to understand how public PD of air pollution affect their preferences for air quality improvement and the influence of the antecedent variables of PD, and (3) to judge the rationality of ICLV model in modeling CE data, PD measurement data and socio-economic characteristics data. The main innovation of this study lies in the fact that public PD perception is considered in exploring the public's preferences for air quality improvement policies, and the ICLV model is applied to include the latent PD identified by considering both individual responses to PD measurement questions and socio-economic characteristics in the discrete choice model. This study will help policy makers better understand the sources of heterogeneity in public preferences for air quality improvement policies, and then formulate more reasonable improvement policies and programs based on public PD perceptions and preferences.

To attain the research purpose mentioned above, the structure framework of the paper is as follows. In the measurement and data collection section, the measurement of PD, the choice experiment design, survey region and data collection are briefly presented, respectively. In the research framework and methodology section, the choice model and the latent variable model are introduced specifically. In the results section, the results from the choice model and the latent variable model are analyzed separately, and the results on the marginal WTP of respondents for the air quality improvement attributes are also discussed. Finally, the theoretical and practical implications of the results obtained in this study are systematically discussed in the conclusions and discussion section.

Measurement and data collection

Measurement of PD

Psychological distance (PD) refers to the distance an individual perceives an event or object (e.g., air pollution) from himself (Trope and Liberman 2003). Many studies have revealed that PD has a significant impact on effective formulation of environmental policy (Fox et al. 2020; Singh et al. 2017). For example, Fox et al. (2020) confirmed reducing the public's PD from environmental pollution would motivate them to provide more environmental action and policy support by conducting an experiment with interactive media; Cheng et al. (2021) analyzed the relationship between PD, attitude and behavior under the context of air pollution, and found respondents who perceive air pollution as close had a positive attitude and greater WTP. However, there is no conclusion as to how public PD affects their choice preferences for air quality improvement policies. This study attempts to fill in the gap, and assumes that PD, like other psychological constructs, is latent and not directly observable. Therefore, it is necessary to identify the psychometric scale of latent PD in the context of air pollution.

Many scholars measure respondents' PD from environmental pollution by presenting a set of question statements in a questionnaire. For example, Liu et al. (2021) measured respondents' PD from environmental pollution through four questions and then developed it into a single paradigm to explore how PD affects respondents' willingness to participate in second-hand online transactions. In the study, respondents were asked how much they agreed with statements like “environmental pollution will occur in the future, affect areas far away from here and people dissimilar to me, and whether it is being polluted.” Referring to the research of Spence et al. (2012) and Liu et al. (2021), this paper finally selects a scale consisting of four questions to quantify the potential PD perception of air pollution after focus group discussion. All four items (PD1-PD4) were assessed using the 5-point Likert scale, in which the five-point responses for the first three items (PD1-PD3) were expressed as ranging from 1 (strongly disagree) to 5 (strongly agree), and the five-point response for the fourth item (PD4) was expressed as ranging from 1 (effects are already being felt now) to 5 (never). After conducting preliminary research, some ambiguous PD problems were corrected to make respondents better understand the PD items, such as “I am afraid that air pollution has a great effect on people similar to me” into “I am afraid that air pollution has a great effect on me,” and the reliability and validity of the construct also passed the test (see Table S3-S4), in which

the Cronbach's α was greater than 0.7 (Cronbach 1951) and the PD was successfully extracted from the scale. The final version of the PD scale can be seen in Table S1.

Choice experiment design

A CE section of the questionnaire was designed to investigate the public's preferences for air quality improvement policies and assess the potential value for air quality. This section mainly presents the respondents with multiple choice sets consisting of different alternatives designed by the different levels of air quality attributes, and the respondents are asked to choose the one they prefer most in each choice set.

In CE studies, the determination of attributes and levels in experimental design directly affects the evaluation of the final research results (Kim et al. 2019). After a comprehensive review of the literature and several consultations with environmental science experts and researchers from the Harbin Municipal Bureau of Ecology and Environment, the relevant attributes and levels of CE for the research questions in this paper were preliminarily determined. Later, focus groups involving local residents, team members and professionals held several discussions on the credibility and rationality of the predetermined attributes and levels. Finally, combining the results of the focus group discussions with the feedback from the preliminary survey, attributes and levels (see Table 1) were determined. In addition, the annual additional taxes paid to government departments was considered as the payment vehicle to assess the potential value of air quality improvement policies in this study, as can be seen from the description of the price attribute. Details about each attribute and level are described below.

• *Good air days*

Good air is not only the material foundation for human survival and development, but also the most equitable public good and the most inclusive well-being for people's livelihoods. In recent years, the state has paid more and more attention to the improvement of air quality. In 2018, the State Council announced a “Three-year Action Plan to Win the Blue Sky Protection Campaign” that included increasing the percentage of days with good air quality each year. The Air Quality Index (AQI) is used as a quantitative indicator describing air pollution levels and their effects on health. In this study, the number of days in a year with AQI less than or equal to 100 was defined as “good air days.” Using 2018 as a baseline, four attribute levels were determined as 60%, 70%, 80%, and 90% respectively.

Table 1 Attributes and levels

Attributes	Descriptions	Levels
Good Air Days	Percentage in the number of good air days per year relative to the status quo	60%* 70% 80% 90%
Heavily Polluted Days	Decrease in annual days with severe haze pollution relative to the status quo	40 days* 30 days 20 days 10 days
Mortality	Percentage decrease in annual premature deaths for air pollution relative to the status quo	Decreased by 0%* Decreased by 10% Decreased by 20% Decreased by 30%
Policy Postponement	Years of postponement in policy effect	5 years* 3 years 1 year
Annual Payment Amount	The annual additional taxes to implement the corresponding policy	RMB 0* RMB 100 RMB 200 RMB 400 RMB 600 RMB 800

* indicates the base level of each attribute

• *Heavily polluted days*

In China, exhaust emissions from heavy polluting enterprises and cars caused severe air pollution problems (Jiang et al. 2018). Particularly in Northeast China, the pollutants produced by open-air straw burning aggravated regional air pollution, making heavy pollution weather occur frequently (Wen et al. 2020). Given the change of the heavily polluted days (which was defined as AQI greater than 200 in this study) in previous years, using the 40 heavily polluted days in 2018 as the status quo, the four levels were identified as 40 days, 30 days, 20 days, and 10 days.

• *Mortality*

One major risk factor for premature deaths worldwide is air pollution. Global ambient air pollution caused millions of premature deaths from environmental fine particulate matter (Khomenko et al. 2021). It is clear that the serious harm caused to human health by air pollution should not be underestimated. Therefore, mortality was considered in this survey as an attribute that represents the negative impact of air pollution on human health. By referring to the results of the related research (Mao et al. 2020; Tang and Zhang 2015), four levels were considered as follows: the mortality caused each year by air pollution was reduced by 0%, 10%, 20%, and 30% relative to the current status quo.

• *Policy postponement*

Any public policy that significantly improves the environment usually requires some time delay to achieve

the final policy effect, depending on financial, material resources, etc. As previously mentioned, the State Council released a three-year action plan for air pollution control. Based on relevant research (Tang and Zhang 2015) and the feedback of focus group discussions, the final levels of the attribute policy postponement were: 5 years, 3 years and 1 year.

• *Annual payment amount*

The annual additional tax is used as the price attribute to assess the respondents' WTP for the improvement attributes in this study. Taxation and voluntary donation can be considered as two kinds of typical payment vehicles when assessing the value of environmental goods using the stated preference approach, where taxation is compulsory but voluntary donation is non-compulsory. Since environmental goods are non-competitive and non-exclusive, compared to voluntary donation, taxation can prevent the emergence of free-riding behavior that causes a certain degree of bias in the welfare estimate (Bateman et al. 2002). In addition, taxation is often used in studies to assess the value of environmental goods such as air quality (Dong and Zeng 2018; Quan and Huang 2016). Therefore, the annual additional tax paid by the public is used as the price attribute in this study. The levels of the price attribute were preliminarily determined based on the reference of relevant research conclusions (Dong and Zeng 2018; Quan 2017) and were revised through the consultations with focus group members and feedback from the preliminary survey. The levels of this price attribute were

finally determined as 0 CNY, 100 CNY, 200 CNY, 400 CNY, 600 CNY, and 800 CNY.

After the attributes and levels are determined, the researcher must determine the number of choice sets presented to the respondents. Generally, a choice set consists of two improvement alternatives and one status quo alternative, in which each alternative is a combination of attributes with different levels. However, if the number of alternatives presented to the interviewees is too large, their cognitive burden will be increased (Breeze et al. 2015). Therefore, a Bayesian D-efficient design with statistically higher efficiency, which requires prior values of parameters to be determined in advance, was applied to simplify the distinct combinations of levels of the above attributes (960) based on the minimum D-error through the NGene software (ChoiceMetrics 2018; Hensher et al. 2015). The prior values used to generate the pre-survey choice tasks were based on the literature and our previous research results. And then, the prior values of the CE design in the final questionnaire were determined based on the pre-survey results. After removing unreasonable and repetitive alternatives by certain command statements, 30 improvement alternatives were obtained, which were then randomly assigned to the 15 choice sets along with a status quo option. All of these 15 choice sets were blocked into 5 versions by randomized blocks design, and then each version including 3 choice sets was presented to every respondent. The process of randomization block design ensures that any preference heterogeneity revealed by final parameter estimation results was not affected by the levels of attributes presented to respondents (Arentze et al. 2003).

The last one in each choice set is the status quo option, meaning that air quality management is maintained at the status quo level and the public does not need to pay additional taxes for this. The other two alternatives generated by CE designs represent varying degrees of improvement in air quality that the public and the government can take a lot of measures to achieve. Respondents' choices among these sets can further reveal the public's WTP and preferences for air quality improvement.

Survey region and data collection

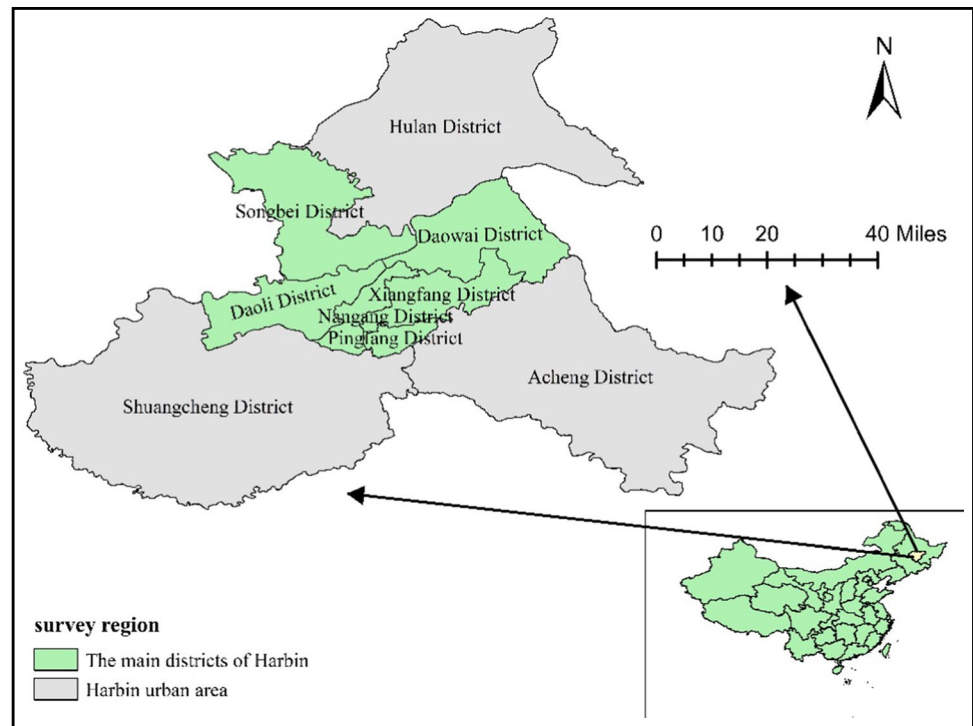
This survey was conducted in Harbin city from Heilongjiang Province, which lies in the northeast of China. In recent years, the air quality in Harbin city has been worrying for residents' health because of coal and crop residue burning as well as industrial waste gas emission, which also bring serious economic losses for the local tourism industry (Hao et al. 2021). During 2014 and 2015, the concentration of NO₂, PM₁₀, PM_{2.5}, and SO₂ from Harbin city was all higher than the average value among 31 capital cities from China, and the heavily

polluted days in Harbin city ranked first among these cities (He et al. 2017). According to the report based on comprehensive indexes of air quality from China's State of the Environment Bulletin (CSEB), Harbin city lay in 51 among 74 large cities in 2017, which further supports the fact that Harbin city suffered from severe air pollution environment. Besides, research from the public's perspective showed that residents living in Northeast China Region had a more severe perception of air pollution than those in other regions and are less satisfied with it (Pu et al. 2019).

Data were collected by well-trained interviewers in the winter of 2019. The six main districts of Harbin were identified as the research areas in this study, as shown in Fig. 1. A small-scale preliminary survey was conducted before the formal survey, and some inaccurate descriptions were corrected based on the respondents' feedback. In addition to the revision of the PD scale and attribute levels, respondents also indicated that direct reporting of annual income would easily lead to inaccurate answers, so monthly income was used instead of annual income in the revised version. The final questionnaire consists of the following three parts: measurement of PD, choice experiment design, and statistics of socio-economic characteristics. A complete version of the questionnaire can be seen in the Table S1. In formal survey, 300¹ complete questionnaires were effectively collected, and the number of questionnaires of each region was determined according to the relative population proportion of each region to all the population of six regions in the "2018 Statistical Yearbook of Harbin." Questionnaire collection was conducted face-to-face with a randomly selected sample in the heart of each city district, and each respondent spent an average of 20 min answering the questions in the questionnaire. Before filling out the questionnaire, the interviewers briefly introduced the attributes and levels of the CE survey and why compulsory tax is needed (details can be seen in the Supplementary materials), so that respondents would then choose the most preferred alternative after careful consideration and weighing. When filling out a questionnaire, the interviewers also timely answered the questions that the respondent did not understand in the questionnaire, and then the respondent was also given a small gift in return. Finally, after removing 16 invalid questionnaires, a total of 284 valid samples were used for data analysis (852 valid observations). Statistical analysis of respondents' socio-economic characteristics and PD items can be found in the Table S2 and Fig. S1.

¹ According to the complete enumeration strategy, the experimental design requires a minimum of 250 respondents to conform to design efficiency (Andreopoulos et al. 2015).

Fig. 1 Research areas map of this paper



Research framework and methodology

To further reveal the motivation of public choice preferences, this study attempts to explore the effect of public PD on preferences for air quality improvement policies by combining the PD scale and the CE survey. However, previous studies have generally used the following two methods to explore the effects of psychological factors on respondents' preferences. One way is to take respondents' responses to indicator questions as a direct measurement of psychological perception, which are then directly incorporated into choice models as free-error explanatory variables (Hagedoorn et al. 2019; Onozaka et al. 2010). In addition, another way is to calculate the factor score of psychological factors through factor analysis of indicator variables, and then these factor scores are incorporated into choice models as free-error explanatory variables (Xu et al. 2020). However, these two methods both generate at least two problems, such as measurement error and correlation with error terms (Hoyos et al. 2015). Therefore, this paper attempts to develop a hybrid model to reasonably incorporate the latent PD.

The Integrated Choice and Latent Variable (ICLV) approach offers a robust framework structure to incorporate PD as a latent variable into the discrete choice model (Potoglou et al. 2015; Vij and Walker 2016), which can make public PD motivation more visible while reducing the estimation bias (Abate et al. 2020; Alemu and Olsen 2019). The model framework is shown in Fig. 2, which consists of two components: discrete choice model and

latent variable model, in which the paths of the structural relation and measurement relation are represented by solid lines and dashed lines, respectively. Respondents' perceived PD of air pollution is measured by their responses to psychometric questions, while it also affects the respondents' utility accompanied by a set of observed air quality attributes. Beyond that, the perceived PD is also a function of the respondents' socio-economic variables.

Choice model

The discrete choice model is subject to the Random Utility Theory (RUM) based on the assumption that the respondents' utility is composed of a deterministic component (V_{nit}) and a stochastic component (ε_{nit}) (McFadden 1973). Under the context of the environment, the deterministic item is assumed to be a linear combination of air quality attributes (X_{nit}) and the interaction terms between the latent variable PD (LV_n) and status options (ASC_0). Psychological factors are often used to explain the status quo effect in CE (Meyerhoff and Liebe U 2009). Hence, the utility of individual n choosing an alternative i in choice scenario t can be written as:

$$U_{nit} = V_{nit} + \varepsilon_{nit} = ASC_0 + \beta' X_{nit} + \zeta' ASC_0 LV_n + \varepsilon_{nit} \quad (1)$$

where ASC_0 is the alternative specific constant representing unobserved average effect of utility in the status quo option,

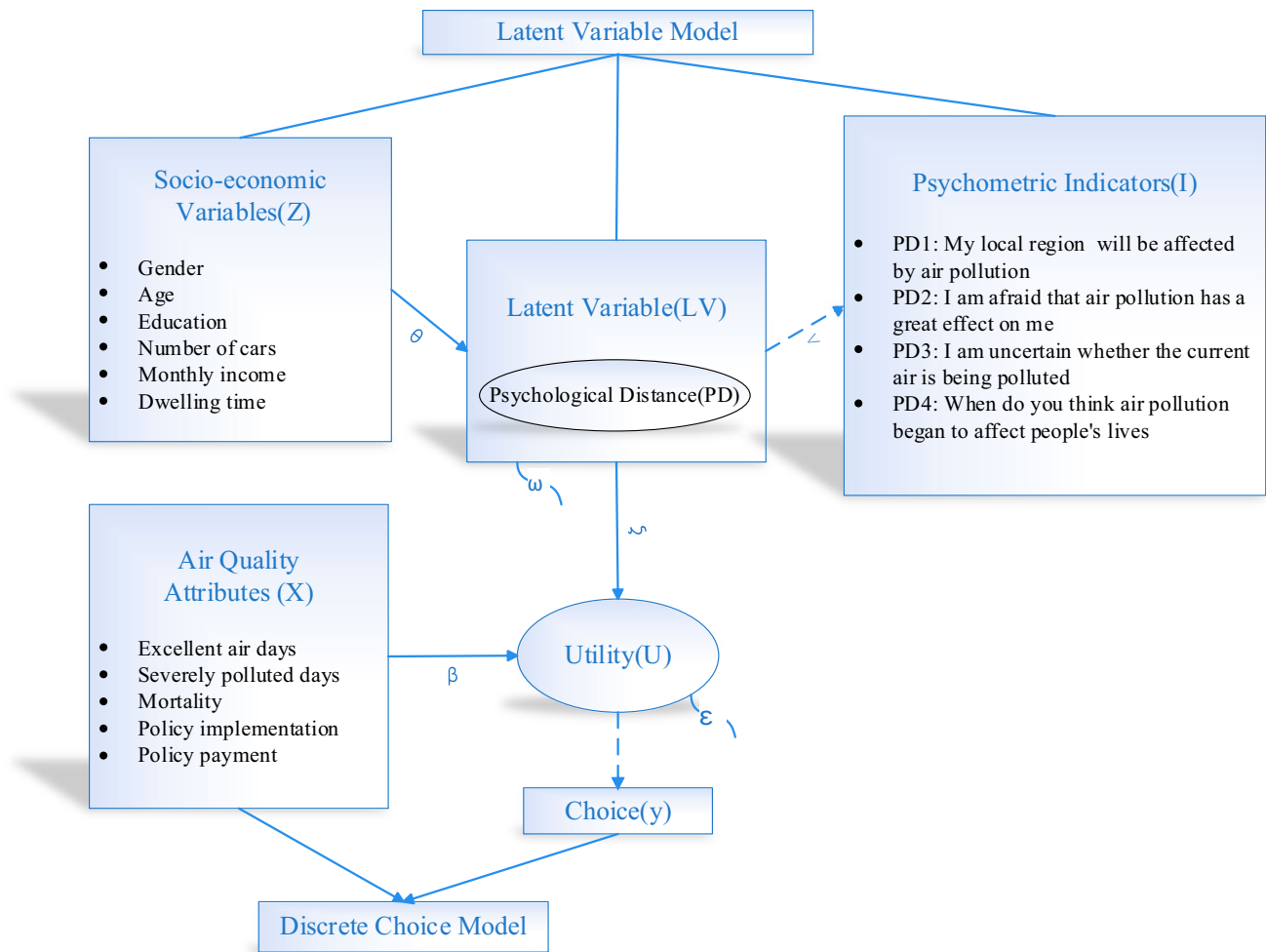


Fig. 2 The ICLV model framework (adapted from (Potoglou et al. 2015))

β' is a coefficient vector indicating the average impact of the air quality attributes on the utility, ζ' is a parameter vector estimating the effect of the interaction between PD and the status quo option on the utility and ϵ_{nit} is an error component that is assumed to follow Type I Extreme Value distribution. The observe probability of the alternative i being selected by the respondent n is expressed by multinomial logit (MNL) model:

$$P(y_{ni} = 1 | X_{nit}, LV_n; \beta', \zeta') = \exp(V_{nit}) / \sum_i \exp(V_{nit}) \quad (2)$$

and

$$y_{ni} = \begin{cases} 1, & \text{if } U_{ni} > U_{ni'} \forall i' \in \{1, \dots, I\} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where choice indicator y_{ni} , with a value equaling 1 when the alternative i is chosen by the respondent n , or 0 otherwise.

The average marginal WTP of respondents for each attribute is calculated based on the parameters estimated in

the choice model. The concrete calculation formula is as follows:

$$WTP_q = -\beta_q / \beta_p \quad (4)$$

where β_q and β_p respectively refer to the estimated coefficients of the improvement attribute x_q and the price attribute x_p .

Latent variable model

The latent variable model is established to identify the above latent PD, in which the first equation is assumed in this paper to be a linear function describing the causal relationship between individual socioeconomic variables and the latent variable PD, so the perceived PD (LV_n) of the respondent n is specified as:

$$LV_n = \theta' Z_n + \sigma \omega_n \quad (5)$$

where Z_n is a vector representing socioeconomic characteristics for the respondent n , θ' is a coefficient vector describing the influence of Z_n on LV_n , σ is a scale parameter related to ω_n , and ω_n is a random error vector assumed to follow the standard normal distribution. Correspondingly, the observed probability of the latent variable PD for the respondent n is estimated by:

$$P(LV_n|Z_n; \theta', \sigma) = \varphi\left(\frac{LV_n - \theta'Z_n}{\sigma}\right) = \varphi(\omega_n) \tag{6}$$

where $\varphi(\cdot)$ denotes a probability density function of the standard normal distribution.

However, the public’s PD of air pollution is an abstract concept, so it is not directly measurable. To capture the PD, we use a group of psychometric problems whose responses are assumed to be linear functions of the PD. Therefore, the measurement equation of indicator r among the total R indicators for the respondent n is shown as follows:

$$I_{rn}^* = \alpha_r + \theta'_r LV_n + \sigma_r \eta_r \tag{7}$$

where α_r is a constant term, θ'_r is the parameter vector reflecting the degree of influence of the latent variable PD on the r^{th} indicator variable, η_r is a random disturbance term, which is assumed to be standard normally distributed, and σ_r is a scale parameter related to η_r .

In this survey, respondents’ answers to the psychometric indicators related to air pollution are collected by using Likert scales. Due to the intrinsic orderliness of Likert scale, the observed results of the r^{th} measurement equation are therefore modeled as an ordered probit model, which has been proved to be able to accurately describe the probabilities of each Likert item in each level (Liddell and Kruschke 2018):

$$I_{rn} = \begin{cases} 1 & \text{if } -\infty < I_{rn}^* < \tau_1 \\ 2 & \text{if } \tau_1 < I_{rn}^* < \tau_2 \\ 3 & \text{if } \tau_2 < I_{rn}^* < \tau_3 \\ 4 & \text{if } \tau_3 < I_{rn}^* < \tau_4 \\ 5 & \text{if } \tau_4 < I_{rn}^* < +\infty \end{cases} \tag{8}$$

where $\tau_1, \tau_2, \tau_3, \tau_4$ are threshold parameters that need to be estimated. To explain the symmetry of the response, we define two positive parameters π_1 and π_2 to determine the four threshold parameters:

$$\begin{aligned} \tau_1 &= -\pi_1 - \pi_2 \\ \tau_2 &= -\pi_1 \\ \tau_3 &= \pi_1 \\ \tau_4 &= \pi_1 + \pi_2 \end{aligned} \tag{9}$$

Hence, the likelihood of the given responses I among R indicators determined by the respondent n is given by the ordered probit model:

$$\begin{aligned} &P(I|LV_n, Z_n; \theta'_r, \sigma_r) \\ &= \prod_R \left(\Phi\left(\frac{\tau_k - (\alpha_r + \theta'_r LV_n)}{\sigma_r}\right) - \Phi\left(\frac{\tau_{k-1} - (\alpha_r + \theta'_r LV_n)}{\sigma_r}\right) \right) \end{aligned} \tag{10}$$

where τ_k, τ_{k-1} are the two threshold parameters for the k^{th} level, and $\Phi(\bullet)$ is the cumulative distribution function (CDF) following standard normally distributed.

The final choice probability of the ICLV model containing a latent variable PD is written as:

$$\begin{aligned} &P(y_n, I|X_{nit}, LV_n, Z_n; \beta', \zeta', \theta', \sigma) \\ &= \int_{\omega_n} P(y_{ni}|X_{nit}, LV_n) P(I|LV_n, Z_n; \theta'_r, \sigma_r) \varphi(\omega_n) d\omega_n \end{aligned} \tag{11}$$

which is the joint estimate for the Eq. (2) in the choice model, the Eq. (6) and the Eq. (10) in the latent variable model over the random error ω_n . In addition, The ICLV model is finally estimated with maximum likelihood by the PandalBiogeme (Bierlaire 2020). The corresponding log-likelihood function is written as:

$$\begin{aligned} &LL(\beta', \zeta', \theta'_r, \sigma_r, \theta', \sigma) \\ &= \sum_{n=1}^N \text{Ln} \int_{\omega_n} L(y_{ni}|\beta', \zeta', LV_n) L(I|LV_n, \theta'_r, \sigma_r) \varphi(\omega_n) d\omega_n \end{aligned} \tag{12}$$

This contains not only the observed probability of choice sequences, but also the probability of given responses to measurement indicators related to the latent variable PD for all the respondents. However, the log-likelihood of the MNL model only provides the probability of individual choices observed. It is necessary to figure out whether incorporating the latent variable PD into the ICLV model can better explain the respondents' choices, so the parameters θ' gotten by maximizing Eq. (12) are fixed in the likelihood function of the choice model component, denoting as θ^* , as shown below:

$$LL_{choice}(\theta^*, \beta', \zeta') = \sum_{n=1}^N \text{Ln} \int_{\omega_n} L(y_{ni}|\beta', \zeta', LV_n) \varphi(\omega_n) d\omega_n \tag{13}$$

where LV_n is a function of θ^* .

Results

Choice model estimates

The choice model is the most important part in the ICLV model, which is estimated simultaneously with two components of the latent variable model. The most widely used discrete choice model is the MNL model without any latent variables, which is also estimated as a reference model in this paper. In addition, to explore whether respondents’ socioeconomic variables would have a direct

effect on their preferences, the model of the direct inclusion of socioeconomic variables in the utility function is also used as a reference model. The estimation results of all the parameters in the above three choice models are presented in Table 2. For air quality attributes, all models report the similar estimation results with consistent signs and approximate value, which shows the applicability and robustness of ICLV model in modeling the data collected in this study.

The coefficient of Good Air Days is significantly positive, indicating that respondents’ utility increases as the number of days with good air quality increases each year. However, the Heavily Polluted Days attribute is significantly and negatively correlated with the respondents’ utility, indicating their utility increases as the number of heavily polluted days decreases. Respondents also value their physical fitness, as can be seen from the positive coefficient of Mortality in Table 2. In addition to these attributes that are directly related to air quality, the years of Policy Postponement of improvement effects also affect individual

utility. Respondents tend to choose the improvement policy that will be implemented soon. Finally, the coefficient of Annual Payment Amount is consistent with the fundamental assumption of the consumer psychology theory. Respondents prefer improvement policies at low prices, and their utility decreases as the additional policy payment associated with the air quality improvement increases. As for the coefficient of alternative specific constant of status quo alternative (ASC_0), the signs of both the MNL and ICLV model are significantly negative, manifesting individuals get a negative utility from the status quo option. In addition, for the interaction term between socioeconomic variables and the status quo alternative, all coefficients are insignificant, indicating that respondents’ socioeconomic characteristics do not have a direct impact on the utility they derive from the hypothetical air quality alternatives.

Attention now turns to the interaction term between the latent variable PD and the status quo alternative in the ICLV model. The results show that the closer the respondents’ PD of air pollution, the more willing they are to choose air

Table 2 Estimated results of the choice models

Variables	MNL model		MNL model with the socioeconomic variables		ICLV model	
	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Air quality attributes						
Good Air Days	0.023***	3.06	0.023***	3.07	0.0198***	2.65
Heavily Polluted Days	-0.0219**	-2.53	-0.0221**	-2.56	-0.0186**	-2.13
Mortality	0.0233***	2.64	0.0239***	2.71	0.0204**	2.28
Policy Postponement	-0.0598*	-1.69	-0.0589*	-1.66	-0.0425	-1.19
Annual Payment Amount	-0.00211***	-5.25	-0.00214***	-5.30	-0.00191***	-4.70
Status quo alternative						
ASC_0	-0.545***	-2.72	0.259	0.34	-0.475*	-1.95
Interaction term with ASC_0						
Impact of socioeconomic characteristic						
Female			-1.77	-0.34		
Education			-0.674	-0.43		
Monthly income			0.727	0.33		
Number of cars			0.00329	0.01		
Dwelling time			-0.482	-0.35		
Impact of latent variable						
PD					2.02*	1.88
Evaluation index						
Log-likelihood(choice model)	-833.410		-825.2164		-829.254	
AIC(choice model)	1678.819		1672.433		1674.508	
BIC(choice model)	1707.304		1724.656		1712.489	
ρ^2 (choice model)	0.110		0.306		0.181	

AIC refers to Akaike Information Criterion, equal to $2k - 2LL$; BIC refers to Bayesian Information Criterion, equal to $-2LL + k \ln(N)$; ρ^2 refers to Rho-square for the model, equal to $1 - LL^*/LL$. Here k means the number of estimated parameters in the choice model and N is the sample size, LL and LL* refers to the Log-likelihood of for the choice model and initial model respectively. And *, **, *** means significant level at 10%, 5%, and 1% level respectively

quality improvement alternatives. In other words, when respondents have a close PD of air pollution, they may consciously take mitigation measures to reduce the deterioration of air quality, which they would otherwise ignore.

To explore whether the latent PD can be reasonably included in the discrete choice model, we report some evaluation indexes. The ICLV model with the latent PD shows the lower AIC and higher ρ^2 . The results not only show a much larger improvement in the fitness effect of the ICLV model with respect to the MNL model but also verify that the respondents' choice preferences for air quality improvement policies are potentially affected by their perceived PD of air pollution. That is, the PD reveals some heterogeneity in individual preferences for air quality improvement policies. Therefore, PD can be considered as an important sign of individual preference heterogeneity in the context of air pollution.

Latent variable model estimates

As mentioned above, PD cannot be directly incorporated into the choice model as an explicit variable for analysis. The latent variable model in this section not only quantifies the respondents' PD of air pollution but also analyzes the influence of its antecedent variables, socioeconomic characteristics, on PD.

Table 3 reports the estimated coefficients for the structure equation. All the coefficients are statistically significant, indicating that these socioeconomic variables have a significant effect on the public's perceived PD of air pollution. More specifically, the results show that the female, respondents' education level and dwelling time lived in Harbin positively affect their perceived PD of air pollution, whereas their monthly income and the number of cars they own negatively affect their perceived PD. In other words, the female and respondents with higher levels of education and longer dwelling time in Harbin perceive air pollution as more severe and therefore have a closer PD of air pollution. However, respondents with higher incomes and more cars have a more distant PD perception of air pollution.

Table 3 Estimated coefficients of the explanatory variables of the PD

Variables	Coefficient (θ')	t-test
Female	0.22**	2.29
Education	0.529***	10.2
Monthly income	-0.0808**	-2.23
Number of cars	-0.29***	-3.86
Dwelling time	0.182***	4.83
σ	1.16***	11.3

*, **, *** means significant level at 10%, 5%, and 1% level respectively

Table 4 shows the estimation results for the measurement equation of the latent variable PD, in which the latent variable PD is significantly positively correlated with the four psychometric indicators. The estimated coefficients (ϑ'_r) capture the different impact of perceived PD on its four measurement variables. And the PD4, asking when air pollution began to affect themselves, is valued the most important indicator compared with other three indicators, indicating the respondents' PD of air pollution is mainly reflected in the perception of time.

In addition, Table 5 presents the two statistically significant positive threshold parameters π_1 and π_2 , which indicate that respondents' responses to the four PD perception measurement items fit well with the ordered probit model proposed in this paper.

Willingness to pay

Based on the estimation results of choice models, the marginal WTP of attributes are calculated. Figure 3 shows the respondents' average marginal WTP for each air quality improvement attribute, respectively. As can be seen in Fig. 3, the WTP of attributes calculated by two choice models are relatively stable with a consistent trend. Respondents are most willing to pay more to reduce the years of policy postponement relative to the other three attributes. Based on the estimation results of the choice model including the

Table 4 Measurement results for the four PD indicators

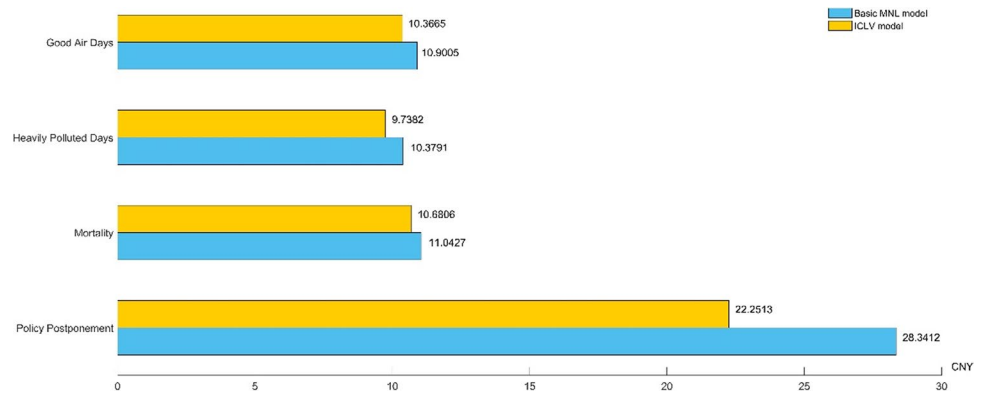
Indicators	ϑ'_r	Estimate (ϑ'_r)	Constant (α_r)	σ_r
PD1	Coefficient	0.532***	-0.125	0.685***
	t-test	11.8	-1.45	11
PD2	Coefficient	0.483***	-0.207**	0.865***
	t-test	11.2	-2.36	12.9
PD3	Coefficient	0.537***	-0.154*	0.65***
	t-test	12.1	-1.82	10.7
PD4	Coefficient	1	0	1

*, **, *** means significant level at 10%, 5%, and 1% level respectively

Table 5 Ordered probit threshold parameters results

Parameters	Coefficient	t-test
π_1	0.590***	13.3
π_2	0.852***	13.9

*, **, *** means significant level at 10%, 5%, and 1% level respectively

Fig. 3 MWTP of improvement attributes

latent PD, respondents are willing to pay 10.37CNY² and 9.74CNY per year for a 1% increase in good air days and one day decrease in heavily polluted days, respectively. In addition, respondents are also willing to pay 10.68CNY for every 1% reduction in premature deaths caused by air pollution each year. Particularly, up to 22.25CNY per year is paid by each respondent for 1 year of reduction in the policy postponement.

Conclusions and discussion

Whether the air quality is good or bad is closely related to our lives. In view of the harm caused by air pollution, people have begun to pay attention to the air quality situation. At this point, understanding the sources of heterogeneity in public preference for air quality improvement policies will help to better implement these policies. The results of this study confirm that public PD significantly affects their choice preferences for air quality improvement policies and the willingness to improve air quality. Air quality improvement policies can be adjusted according to the public's PD perception and preferences for air quality improvement so as to conduct effective risk communication and perfect the practical path for public participation in air quality governance.

To help policy makers understand how public PD motivates them to engage in air quality improvement, the perceived PD is incorporated into the discrete choice model. The research results suggested that, compared with the MNL model without latent variables, the ICLV model incorporating the latent PD prove to have higher model fitness.

Empirical results in this paper confirm that respondents' perceived PD of air pollution significantly affects their choice preferences for air quality improvement policies.

The closer psychological distance (PD) of air pollution promotes respondents to show greater support for air quality improvement policies. This is consistent with previous findings of Liu et al. (2021), which shows that consumers having a closer PD from environmental pollution are more willing to participate in second-hand online transaction, with a strong environmental awareness. This may be because respondents who have a closer PD of air pollution perceive the risks posed by air pollution to be stronger, so that when they consider the serious physical and mental harm that air pollution poses to themselves, they view air pollution as an urgent problem and feel more personally responsible for the problem, thus demonstrating more environmental behavior and greater policy support (Fox et al. 2020). Therefore, disseminating information about air pollution to individuals will have potential implications for air quality improvement, especially those who perceive air pollution at a closer PD are more willing to participate in the control and management of air pollution than those who perceive it at a more distant PD. For local governments, taking some measures to adjust public PD of air pollution will be of great significance in the management and control of air pollution. For example, the government can reduce the public's PD by increasing the visual publicity of the harm of air pollution to their lives and work, as well as to those around them. It is also necessary to timely disclose to the public the implementation effects of air quality improvement policies, which will not only increase the public's trust in the government, but also stimulate the public to adopt behaviors conducive to air quality improvement in their daily lives as they think it brings them to perceive air pollution at a closer PD.

The results confirm that individuals' socio-economic characteristics affect their perceived PD of air pollution. Compared to men, women perceive air pollution at a closer PD, which in turn make them more inclined to focus on the current air quality and improve it. This may be because women are more attentive to details, and this trait can lead to greater concern about local air pollution phenomena, as well as further promote their improvement behavior. Meanwhile,

² CNY: currency of China, 1CNY=0.145USD.

our study results also indicate a positive correlation between respondents with higher levels of education and closer PD of air pollution. In general, well-educated people are also more likely to focus on air quality conditions and the implementation of related improvement policies in their lives. As we expected, the longer respondents live in Harbin, the more sensitive they become to the severe effects of local air pollution on them, so they are willing to pay a certain amount to protect air quality. Surprisingly, respondents with higher monthly incomes and more cars have a more distant perceived PD of local air pollution and thus have a more satisfied attitude about the current air quality status. The cause may be that high-income people are often able to afford the health expenses caused by air pollution, so compared to low-income people, they are not sensitive to the risk of air pollution, so they have a distant PD of air pollution and are satisfied with the status quo of air quality. Likewise, the similar cause is also shown for the coefficient of the number of cars. In a word, for men and those with lower levels of education, the government should raise their awareness about the protection of local air quality by informing them of the fact that air pollution is all around them. For high-income people, the government should also raise their awareness of air pollution concerns and promote their contribution to improving the current air quality by highlighting the dangers of local air pollution to them and their families.

In this paper, a CE survey is used to provide hypothetical policy scenarios consisting of different levels of air quality attributes to capture public preferences for air quality improvement policies after carefully weighing these attribute levels. In particular, a price attribute is used to capture the respondents' WTP for air quality improvement.

Focusing on the positive value of respondents' marginal WTP for air quality improvement attributes, which not only indicates that respondents are willing to support the improvement policies related to air quality, but also reveals the enormous economic value that clean air provides. The government can adjust policies accordingly based on the findings, thereby promoting sustainable management of air quality. Firstly, it is worth noting that respondents attach great importance to how many years improvement policies will take to implement (28.3412 CNY per year). This may be due to the public's urgent need for a living environment with good air quality. Therefore, the government should shorten the policy postponement period to meet the needs of the public by increasing the financial input for environmental improvement and improving the efficiency of the use of financial funds. Beyond this, developing more reasonable and effective air quality improvement policies based on the results of this study will also accelerate the implementation of these policies. Secondly, as air pollution poses a serious threat to public health, the

public is also concerned about the annual premature deaths due to air pollution, and is willing to pay 11.0427CNY per year for a 1% reduction in mortality. To reduce the number of premature deaths, the government must tighten controls on a large number of pollution sources that are expected to play a major role and are difficult to control in the future. For example, the government should set strict emissions standards and supervise their implementation. At the same time, improving public understanding of how air pollution contributes to the risk of disease and death is also a crucial step. In addition, the public is also willing to pay 10.9005CNY per year for every one percent increase in good air days. Therefore, various countermeasures on encouraging the public to engage in environmental governance in their daily lives should be taken to meet their high demand for clean air, such as organizing regular volunteer activities to protect the environment. Finally, the government should also focus on days of heavy pollution (10.3791CNY per year) caused by emissions from coal-fired heating during long heating period, for example through using cleaner energy instead.

In summary, the contributions of this paper can be mainly reflected in theory and practice. In theory, a more robust ICLV model is used to link CE studies with PD in the context of air pollution, thus forming a new theoretical framework to explore the role of PD in air quality improvement policies. In practice, this study confirms not only the public's willingness to pay for air quality improvement, but also the importance of public PD in the field of air pollution control and management. Based on this, policy makers can formulate more effective and accurate policies and measures to promote air quality improvement work. In addition, this paper also contributes to the literature in drawing attention to PD as an important factor affecting individual preferences in air quality improvement.

Although this study has made some important contributions, there is still some room for further development. Firstly, although the conclusions based on this study have important insights for policy makers on the air pollution control in cities similar to Harbin and provide a reference for the research on the psychological motivation of public preferences, whether they are applicable to other areas still needs to be supported by more empirical studies in other areas affected by air pollution. Secondly, although the survey results can be viewed as sample evidence sufficient to examine the potential relationship between psychological distance and preference heterogeneity, future studies should follow a more rigorous sampling procedure to make the sample more representative. Thirdly, during the survey, the respondents were told the survey results could be used for air pollution treatment policies to enhance the effectiveness of the results. However, emphasizing the consequences of responses perceived by respondents in this way may be

insufficient and may lead some respondents to feel that their responses may not be very important. Future research can consider more effective survey measures to increase the respondents' perceived importance of their own responses. Fourthly, this study ignores the test of the potential correlation between attributes before the formal investigation, but there is no direct evidence to prove that ignoring this test will affect the reliability of the choice tasks and thus affect the validity of the survey results. However, in order to improve the reliability of the research results, it is necessary to further explore this potential problem in subsequent research. Fifthly, this study explores the public's average preferences for attributes related to air quality, but it is not clear whether there are differences in preferences for attributes among groups with different PD of air pollution. Therefore, future studies can be carried out to explore the effect of public PD on the heterogeneity of preferences for attributes based on other models. Finally, it also makes sense to study the impact of factors such as the level of economic and social development and public health on the public's WTP for air quality improvement.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s11356-023-25683-5>.

Acknowledgements This study was financially supported by the National Natural Science Foundation of China under Grant [71874026, 72104171].

Author contribution *Yuehua Wei & Biqi Mao*: Investigation, Funding acquisition, Conceptualization, Software, Methodology, Formal analysis, Writing—original draft, Writing—review & editing. *Lishan Xu*: Investigation, Writing—review & editing. *Changlin Ao*: Resources, Data curation, Funding acquisition, Writing—review & editing.

Funding This study was financially financed by the National Natural Science Foundation of China under Grant [71874026, 72104171].

Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

- Aaditya B, Rahul TM (2021) Psychological impacts of COVID-19 pandemic on the mode choice behaviour: A hybrid choice modelling approach. *Transp Policy* 108:47–58. <https://doi.org/10.1016/j.tranpol.2021.05.003>
- Abate TG, Börger T, Aanesen M, Falk-Andersson J, Wyles KJ, Beaumont N (2020) Valuation of marine plastic pollution in the European Arctic: Applying an integrated choice and latent variable model to contingent valuation. *Ecol Econ* 169:106521. <https://doi.org/10.1016/j.ecolecon.2019.106521>
- Alemu MH, Olsen SB (2019) Linking Consumers' Food Choice Motives to their Preferences for Insect-based Food Products: An Application of Integrated Choice and Latent Variable Model in an African Context. *J Agric Econ* 70:241–258. <https://doi.org/10.1111/1477-9552.12285>
- Andreopoulos D, Damigos D, Comiti F, Fischer C (2015) Handling preference heterogeneity for river services' adaptation to climate change. *J Environ Manage* 160:201–211. <https://doi.org/10.1016/j.jenvman.2015.06.015>
- Arentze T, Borgers A, Timmermans H, DelMistro R (2003) Transport stated choice responses: effects of task complexity, presentation format and literacy. *Trans Res Part e: Log Trans Rev* 39:229–244. [https://doi.org/10.1016/s1366-5545\(02\)00047-9](https://doi.org/10.1016/s1366-5545(02)00047-9)
- Aunan K, Hansen MH, Wang S (2017) Introduction: Air Pollution in China. *China Quart* 234:279–298. <https://doi.org/10.1017/s0305741017001369>
- Bateman IJ, Carson RT, Day B, Hanemann WM, Hanley N, Hett T, Lee MJ, Loomes G, Mourato S, Özdemiroglu E, Pearce DW, Sugden R, Swanson J (2002) *Economic Valuation with Stated Preference Techniques: A Manual*. Edward Elgar, UK
- Bickerstaff K (2004) Risk perception research: socio-cultural perspectives on the public experience of air pollution. *Environ Int* 30:827–840. <https://doi.org/10.1016/j.envint.2003.12.001>
- Bierlaire M (2020) A short introduction to Pndas Biogeme. TRANSPOR publications. <http://infoscience.epfl.ch/record/283453>. Accessed 19 Dec 2018
- Breeze TD, Bailey AP, Potts SG, Balcombe KG (2015) A stated preference valuation of the non-market benefits of pollination services in the UK. *Ecol Econ* 111:76–85. <https://doi.org/10.1016/j.ecolecon.2014.12.022>
- Brügger A (2020) Understanding the psychological distance of climate change: The limitations of construal level theory and suggestions for alternative theoretical perspectives. *Glob Environ Chang* 60:102023. <https://doi.org/10.1016/j.gloenvcha.2019.102023>
- Cao S, Lv Y, Zheng H, Wang X (2014) Challenges facing China's unbalanced urbanization strategy. *Land Use Policy* 39:412–415. <https://doi.org/10.1016/j.landusepol.2013.12.004>
- Cheng Y, Ao C, Mao B, Xu L (2021) Influential factors of environmental behavior to reduce air pollution: integrating theories of planned behavior and psychological distance. *J Environ Plan Manag* 1–21. <https://doi.org/10.1080/09640568.2021.1973972>
- ChoiceMetrics (2018) Ngene 1.2 User Manual and Reference Guide: the Cutting Edge in Experimental Design. <http://www.choice-metrics.com/>. Accessed 30 Jan 2018
- Cronbach LJ (1951) Coefficient Alpha and the Internal Structure of Tests. *Psychometrika* 16:297–334. <https://doi.org/10.1007/BF02310555>
- Dong GH (2019) Ambient air pollution in China. *Respirology* 24:626–627. <https://doi.org/10.1111/resp.13583>
- Dong K, Zeng X (2018) Public willingness to pay for urban smog mitigation and its determinants: A case study of Beijing, China. *Atmos Environ* 173:355–363. <https://doi.org/10.1016/j.atmosenv.2017.11.032>
- Fox J, McKnight J, Sun Y, Maung D, Crawfis R (2020) Using a serious game to communicate risk and minimize psychological distance regarding environmental pollution. *Telemat Inform* 46:101320. <https://doi.org/10.1016/j.tele.2019.101320>
- Hagedoorn LC, Brander LM, van Beukering PJH, Dijkstra HM, Franco C, Hughes L, Gilders I, Segal B (2019) Community-based adaptation to climate change in small island developing

- states: an analysis of the role of social capital. *Climate Dev* 11:723–734. <https://doi.org/10.1080/17565529.2018.1562869>
- Hao Y, Niu X, Wang J (2021) Impacts of haze pollution on China's tourism industry: A system of economic loss analysis. *J Environ Manag* 295:113051. <https://doi.org/10.1016/j.jenvman.2021.113051>
- He J, Gong S, Yu Y, Yu L, Wu L, Mao H, Song C, Zhao S, Liu H, Li X, Li R (2017) Air pollution characteristics and their relation to meteorological conditions during 2014–2015 in major Chinese cities. *Environ Pollut* 223:484–496. <https://doi.org/10.1016/j.envpol.2017.01.050>
- Hensher DA, Rose JM, Greene WH (2015) *Applied Choice Analysis*, 2nd edn. Cambridge University Press, Cambridge
- Hoyos D, Mariel P, Hess S (2015) Incorporating environmental attitudes in discrete choice models: an exploration of the utility of the awareness of consequences scale. *Sci Total Environ* 505:1100–1111. <https://doi.org/10.1016/j.scitotenv.2014.10.066>
- Jiang N, Li Q, Su F, Wang Q, Yu X, Kang P, Zhang R, Tang X (2018) Chemical characteristics and source apportionment of PM_{2.5} between heavily polluted days and other days in Zhengzhou, China. *J Environ Sci (china)* 66:188–198. <https://doi.org/10.1016/j.jes.2017.05.006>
- Jing Y, Xu W, Guo S, Zhang Y (2020) Analysis of Choice Behaviors of Railway Shippers for Freight Services Based on a Fuzzy Integrated Choice and Latent Variable Model. *IEEE Access* 8:64399–64410. <https://doi.org/10.1109/access.2020.2984626>
- Khan SU, Khan I, Zhao M, Khan AA, Ali MAS (2019) Valuation of ecosystem services using choice experiment with preference heterogeneity: A benefit transfer analysis across inland river basin. *Sci Total Environ* 679:126–135. <https://doi.org/10.1016/j.scitotenv.2019.05.049>
- Khomenko S, Cirach M, Pereira-Barboza E, Mueller N, Barrera-Gómez J, Rojas-Rueda D, de Hoogh K, Hoek G, Nieuwenhuijsen M (2021) Premature mortality due to air pollution in European cities: a health impact assessment. *Lancet Planet Health* 5:e121–e134. [https://doi.org/10.1016/s2542-5196\(20\)30272-2](https://doi.org/10.1016/s2542-5196(20)30272-2)
- Kim H-J, Kim J-H, Yoo S-H (2019) Social acceptance of offshore wind energy development in South Korea: Results from a choice experiment survey. *Renew Sustain Energy Rev* 113:109253. <https://doi.org/10.1016/j.rser.2019.109253>
- Li J, Yang X, Liang Z, Tan L (2004) Economic loss of ecological destruction of land resources in the process of urbanization. *J Chongqing Univ* 27:114–117 (in Chinese)
- Li L, Xia XH, Chen B, Sun L (2018) Public participation in achieving sustainable development goals in China: Evidence from the practice of air pollution control. *J Clean Prod* 201:499–506. <https://doi.org/10.1016/j.jclepro.2018.08.046>
- Liddell TM, Kruschke JK (2018) Analyzing ordinal data with metric models: What could possibly go wrong? *J Exp Soc Psychol* 79:328–348. <https://doi.org/10.1016/j.jesp.2018.08.009>
- Liu W, Shao W, Wang Q (2021) Psychological distance from environmental pollution and willingness to participate in second-hand online transactions: An experimental survey in China. *J Clean Prod* 281:124656. <https://doi.org/10.1016/j.jclepro.2020.124656>
- Mao B, Ao C, Wang J, Sun B, Xu L (2020) Does regret matter in public choices for air quality improvement policies? A comparison of regret-based and utility-based discrete choice modelling. *J Clean Prod* 254:120052. <https://doi.org/10.1016/j.jclepro.2020.120052>
- McFadden D (1973) Conditional logit analysis of qualitative choice behavior. In: Zarembka P (ed) *Frontiers in Econometrics*. Academic Press, pp 105–142
- Meyerhoff J, Liebe U (2009) Status Quo Effect in Choice Experiments: Empirical Evidence on Attitudes and Choice Task Complexity. *Land Econ* 85:515–528. <https://doi.org/10.3368/le.85.3.515>
- Mir HM, Behrang K, Isaai MT, Nejat P (2016) The impact of outcome framing and psychological distance of air pollution consequences on transportation mode choice. *Transp Res Part d: Transp Environ* 46:328–338. <https://doi.org/10.1016/j.trd.2016.04.012>
- Mohammadi A, Kermanshah M, Moeinaddini A (2021) Investigation of safety attitude on passenger vehicle type choice: An integrated choice and latent variable (ICLV) approach. *IATSS Res* 45:336–346. <https://doi.org/10.1016/j.iatssr.2021.02.003>
- Oltra C, Sala R (2016) Perception of risk from air pollution and reported behaviors: a cross-sectional survey study in four cities. *J Risk Res* 21:869–884. <https://doi.org/10.1080/13669877.2016.1264446>
- Onozaka Y, Nurse G, Thilmany McFadden D (2010) Defining Sustainable Food Market Segments: Do Motivations and Values Vary by Shopping Locale? *Am J Agr Econ* 93:583–589. <https://doi.org/10.1093/ajae/aaq152>
- Potoglou D, Palacios J-F, Feijóo C (2015) An integrated latent variable and choice model to explore the role of privacy concern on stated behavioural intentions in e-commerce. *J Choice Model* 17:10–27. <https://doi.org/10.1016/j.jocm.2015.12.002>
- Pu S, Shao Z, Fang M, Yang L, Liu R, Bi J, Ma Z (2019) Spatial distribution of the public's risk perception for air pollution: A nationwide study in China. *Sci Total Environ* 655:454–462. <https://doi.org/10.1016/j.scitotenv.2018.11.232>
- Quan S (2017) Using choice experiment to evaluate air quality in Beijing. *China Popul Resour Environ* 27:46–55 ((in Chinese))
- Quan S, Huang B (2016) Embedding Effects in Evaluation of Multiple Environmental Policies—Evidences from Beijing's Haze and Sand Control Policies. *China Ind Econ* 23–39. <https://doi.org/10.19581/j.cnki.ciejournal.2016.08.003>
- Singh AS, Zwickle A, Bruskotter JT, Wilson R (2017) The perceived psychological distance of climate change impacts and its influence on support for adaptation policy. *Environ Sci Policy* 73:93–99. <https://doi.org/10.1016/j.envsci.2017.04.011>
- Spence A, Poortinga W, Pidgeon N (2012) The psychological distance of climate change. *Risk Anal* 32:957–972. <https://doi.org/10.1111/j.1539-6924.2011.01695.x>
- Sun X, Zhang L, Dong Y, Zhu L, Wang Z, Lu J (2021) Source Apportionment and Spatial Distribution Simulation of Heavy Metals in a Typical Petrochemical Industrial City. *Environ Sci* 42:1093–1104. <https://doi.org/10.13227/j.hjcx.202008007>
- Tang C, Zhang Y (2015) Using discrete choice experiments to value preferences for air quality improvement: the case of curbing haze in urban China. *J Environ Plann Manag* 59:1473–1494. <https://doi.org/10.1080/09640568.2015.1079518>
- Trope Y, Liberman N (2003) Temporal construal. *Psychol Rev* 110:403–421. <https://doi.org/10.1037/0033-295x.110.3.403>
- Vij A, Walker JL (2016) How, when and why integrated choice and latent variable models are latently useful. *Trans Res Part b: Methodological* 90:192–217. <https://doi.org/10.1016/j.trb.2016.04.021>
- Wen X, Chen W, Chen B, Yang C, Tu G, Cheng T (2020) Does the prohibition on open burning of straw mitigate air pollution? An empirical study in Jilin Province of China in the post-harvest season. *J Environ Manag* 264:110451. <https://doi.org/10.1016/j.jenvman.2020.110451>
- Xu L, Ao C, Mao B, Cheng Y, Sun B, Wang J, Liu B, Ma J (2020) Which is more Important, Ecological Conservation or Recreational Service? Evidence from a Choice Experiment in Wetland Nature Reserve Management. *Wetlands* 40:2381–2396. <https://doi.org/10.1007/s13157-020-01348-8>
- Yin H, Pizzol M, Jacobsen JB, Xu L (2018) Contingent valuation of health and mood impacts of PM_{2.5} in Beijing, China. *Sci Total Environ* 630:1269–1282. <https://doi.org/10.1016/j.scitotenv.2018.02.275>

- Yoo SH, Kwak SJ, Lee JS (2008) Using a choice experiment to measure the environmental costs of air pollution impacts in Seoul. *J Environ Manag* 86:308–318. <https://doi.org/10.1016/j.jenvman.2006.12.008>
- Zhao Y, Tan Y, Feng S (2020) Does reducing air pollution improve the progress of sustainable development in China? *J Clean Prod* 272:122759. <https://doi.org/10.1016/j.jclepro.2020.122759>
- Zheng S, Wang J, Sun C, Zhang X, Kahn ME (2019) Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nat Hum Behav* 3:237–243. <https://doi.org/10.1038/s41562-018-0521-2>

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