Southeast Asian Journal of Economics Vol.13(3), December 2025:
Received: August 15, 2024
Revision: October 19, 2024
Accepted: March 3, 2025

Valuing Health Effects of Air Pollution in Northern Thailand: Case Study of Urban Residents

Warawut Ruankham

Sustainability and Entrepreneurship Research Center (SERC), Economics Major,
School of Management, Mae Fah Luang University, Thailand.
Corresponding author: Warawut.rua@mfu.ac.th

Abstract

Air pollution is a critical issue in rapidly developing regions, including Northern Thailand. This study estimates the health effects of air pollution and residents' willingness to pay (WTP) for respiratory illness prevention. A survey of 480 respondents across eight provinces in Northern Thailand during December 2023 to May 2024, using Contingent Valuation Methods, finds that individual WTP was an average of 367 THB (11 USD) annually for improving air quality and preventing illness. Regional variations in WTP are observed, with Chiang Mai having the highest and Lamphun the lowest. Key factors influencing WTP include gender, age, income, cost of prevention, perception, and pollution acknowledgement. The findings underscore the high value residents place on cleaner air and highlight the need for targeted financial measures, regional smog mitigation, and enhanced public awareness to address air pollution effectively.

Keywords: PM2.5, air pollution, contingent valuation method (CVM), willingness to pay (WTP), financial measures, Northern Thailand.

1. Introduction

Air pollution has emerged as a critical environmental and public health issue globally, with its effects particularly pronounced in rapidly developing countries (Almetwally et al., 2020). In Northern Thailand, a region renowned for its natural beauty and cultural heritage, air pollution, especially fine particulate matter (PM2.5) during the dry season, has reached severe levels in recent years (Pasukphun et al., 2018). According to the Pollution Control Department of Thailand, the 24-hour average concentration of particulate matter (PM2.5) in Northern Thailand was recorded at 56.43 $\mu g/m^3$ from January 1 to May 31, 2024, significantly exceeding the World Health Organization's (WHO) recommended guideline of 5 $\mu g/m^3$. This alarming level parallels that of some of the world's most polluted cities, including Delhi and Beijing (Dong et al., 2021). Key sources of air pollution in the Northern region stemmed from agricultural burning, forest fires, and slash-and-burn practices (Moran et al., 2019; Phairuang et al., 2017). These local burning activities, compounded with transboundary pollution from neighboring areas, necessitate a comprehensive approach to address both domestic and cross-border pollution effectively (Phairuang et al., 2017).

PM2.5 air pollution poses a serious health risk, leading to a range of debilitating symptoms that significantly impact overall well-being and quality of life (Abidin et al., 2023). Exposure to these fine particles can lead to respiratory illnesses and symptoms such as dry cough, sore throat, and runny nose (Nezis et al., 2022). The health impacts could also extend to the cardiovascular system, manifesting in symptoms like shortness of breath, wheezing, and chest pain (Bergstra et al., 2018). These severe health risks emphasize the urgent need for effective interventions to safeguard public health and enhance the well-being of citizens (Alberini et al., 1997; Bernstein et al., 2004; Kurt et al., 2016; Padmanabha et al., 2021).

The foundation of willingness to pay (WTP) lies in the Contingent Valuation Method (CVM), which employs hypothetical scenarios to elicit monetary valuations for non-market goods based on Hanemann's Random Utility Theory (Hanemann, 1984). Changes in environmental quality, such as reductions in PM2.5 levels, translate into changes in utility, which individuals express through their WTP for improvements or their willingness to accept compensation for deteriorations (Bateman et al., 2002). This measure captures the trade-off between financial resources and environmental benefits while keeping overall utility constant. WTP is also used to evaluate the economic costs and benefits of air pollution improvement by quantifying the public's valuation of health improvements and cleaner air (Delucchi et al., 2002; Pu et al., 2019; Syuhada et al., 2023). Thus, WTP is particularly valuable for crafting policy interventions to address the air pollution issue (Sterner & Coria, 2013).

Empirically, research on WTP has been conducted in various countries to evaluate public preferences for environmental improvements. For instance, studies in Taiwan, Malaysia, China, India, Pakistan, and Sweden have estimated WTP for air quality enhancement through environmental taxes and voluntary contributions (Ain et al., 2021; Alberini et al., 1997; Bernstein et al., 2004; Kurt et al., 2016; Padmanabha et al., 2021; Wang & Mullahy, 2006; Wang et al., 2015; Yu & Abler, 2010). These investigations highlight the relevance of WTP in valuing non-market benefits and guiding policy design to lower air pollution. In Thailand, prior research (Phairuang et al., 2017; Tantiwat et al., 2021) has largely concentrated on the central region, with an emphasis on macro-level evaluations, aggregate assessments, and policy-driven initiatives. These studies primarily explore broader regulatory frameworks and nationwide strategies, often overlooking localized perspectives and individual preference levels. In contrast, this study shifts the focus to Northern Thailand, a region that frequently experiences severe air pollution, yet remains underexplored. By examining individual-level preferences and WTP for air quality improvements, this research provides a more granular understanding of public perception, financial burden, and the potential for targeted interventions in the region.

To address these gaps, this study's primary objective is to estimate the WTP of Northern Thailand's urban residents for improved air quality. By surveying 480 respondents across eight provinces, the research also identifies key determinants of WTP, including socioeconomic characteristics, health impact perceptions, and the costs associated with illness prevention. The remainder of this paper is organized as follows: The literature review examines existing studies on WTP and environmental valuation; the methodology section outlines the econometric approach and survey design across eight provinces; the findings section presents key results, including average WTP, regional variations, and influencing factors; and the conclusion discusses the policy implications, emphasizing the need for targeted interventions to address air pollution in Northern Thailand.

2. Literature Review

2.1 WTP for Air Pollution

The existing literature on WTP for air pollution reduction highlights diverse regional and economic perspectives on addressing air pollution, with studies spanning across Asia, Africa, Europe, and other regions. In Asia, studies conducted in Taiwan, China, Thailand, and Pakistan reflect varied levels of WTP depending on local income levels and the health impacts associated with air pollution. For instance, Alberini et al. (1997) found Taiwanese respondents willing to pay $39.20 through voluntary contributions, while Chinese studies revealed a wider range. Liu et al. (2018) reported that 53% of respondents would pay to improve air quality, and Li and Hu (2018) found an average WTP of $14 per month through environmental tax surcharges. Thailand's studies also illustrate regional concerns, with WTP estimates reaching $62 per year (Tantiwat et al., 2021).

In Africa, research by Donfouet et al. (2015) in Cameroon and Diallo and Seck (2023) in Dakar shows more modest WTP levels, likely constrained by household income, as reflected in Cameroon's average of \$0.42 per month. Interestingly, in Dakar, the introduction of a tax on utilities raised WTP to \$5.6 monthly. Maloma and Sekatane's (2014) study in South Africa found a slightly higher WTP of \$6.91 annually through voluntary contributions, revealing both economic limitations and environmental interests in the region.

European findings differ notably, with Carlsson and Johansson-Stenman (2000) reporting a high WTP in Sweden of \$184 annually for a significant reduction in pollutants, suggesting stronger environmental policies and higher income levels. Similarly, Halvorsen's (1996) study in Norway found a WTP of \$107.12 through income taxes, aligning with European tendencies toward structured environmental funding mechanisms. In contrast, French respondents in Lera-López et al. (2014) were unwilling to pay a compulsory tax for pollution reduction, perhaps reflecting regional differences in public acceptance of environmental taxation.

While existing studies offer valuable insights into WTP across different regions, there is a significant gap in the literature when it comes to Northern Thailand, a region facing severe air pollution challenges, particularly from seasonal smog. Prior research in Thailand applied meta-analysis for mortality risk rising from air pollution and found that the cost of mortality is around 0.74 to 1.32 million USD annually (Vassanadumrongdee et al., 2004). Tantiwat et al.'s (2021) study conducted in Bangkok quantified the economic benefit of air quality improvements at approximately 18.8 billion THB per year. Phairuang et al. (2017) studied the influence of agricultural activities, forest fires, and agro-industries on air quality in Thailand. Vichit-Vadakan and Vajanapoom (2011) and Phosri et al. (2019) studied the health impact and respiratory and cardiovascular diseases from air pollution in Bangkok and the industrial areas. However, these studies have often focused on central areas of Thailand and on aggregate assessments or policy-driven initiatives rather than individual preferences or households at the local level. This study differentiates itself by carefully measuring individual WTP across eight provinces in Northern Thailand, incorporating individual socioeconomic characteristics, air pollution acknowledgement, health impact perceptions, and the cost of prevention. Understanding the residents' WTP for cleaner air is crucial for crafting policies that align with local income levels, health concerns, and public attitudes toward environmental investments.

2.2 Key Determinants of WTP

Table 2 depicts the key determinants and control variables related to WTP to prevent health effects and air quality improvements. One of the most significant predictors of WTP is health condition, particularly the experience of pollution-related health issues. Studies have shown that individuals with health conditions stemming from poor air quality, such as respiratory or cardiovascular problems, demonstrate a notably higher WTP for air quality improvements than their healthier counterparts (Hammitt & Zhou, 2006; Wang et al., 2015; Ortiz et al., 2009). Individuals facing direct health consequences from pollution often perceive cleaner air as a means of alleviating their suffering or preventing further deterioration, thus motivating them to invest financially in pollution reduction efforts. In contrast, healthier individuals, who may feel less vulnerable to air quality impacts, typically exhibit lower motivation to contribute financially. Perceived air pollution and acknowledgement also serve as crucial determinants. Research finds that individuals who view major sources of pollution, e.g., the Electricity Generating Authority of Thailand (EGAT), biomass burning, transportation, household activities, and small factories, as significant threats are more likely to express WTP for air quality improvement. This positive association suggests that individuals with heightened awareness of specific pollution sources recognize the need for mitigation and are willing to support it financially (Srisawasdi et al., 2021; Thanh & Lefevre, 2000, 2001). In addition, respondents identifying biomass burning or heavy transportation as key sources of pollution may see a tangible link between their financial support and potential reductions in these activities, thereby fostering a stronger commitment to paying for air quality initiatives (Yang et al., 2018; Li et al., 2023; Zhao et al., 2018). Another significant determinant is satisfaction with current air quality and local government management of air quality. Studies indicate that individuals who are content with the current state of atmospheric quality or who believe that local authorities are effectively managing air pollution display a markedly lower WTP. This inverse relationship suggests that when people perceive air quality as acceptable or believe that government efforts are sufficient, they are less motivated to contribute financially toward further improvements (Luechinger, 2007; Wei & Wu, 2017; Liu et al., 2016). This finding underscores the importance of public perception, as individuals who trust the adequacy of existing air quality measures may see additional payments as redundant or unnecessary, reducing their financial commitment to pollution control.

To address endogeneity bias, researchers have introduced control variables to account for socioeconomic and other factors influencing WTP. Age, for instance, is often linked to higher WTP, as older individuals may exhibit greater health awareness or disposable income, enabling them to prioritize air quality improvements (Hu & Liao, 2023; Huang et al., 2018; Vassanadumrongdee & Matsuoka, 2005). Similarly, income and expenditure consistently show positive correlations with WTP, reflecting the capacity of wealthier individuals to support public goods like clean air (Yoo et al., 2008; Shao et al., 2018; Wang et al., 2016). Gender differences also play a role, with some studies suggesting that males may demonstrate a higher WTP due to differing risk perceptions and priorities (Guo et al., 2020; Filippini & Martínez-Cruz, 2016). Lastly, education emerges as a significant factor, with higher educational attainment enhancing understanding of pollution’s impacts and motivating greater financial support for mitigation efforts (Hu & Liao, 2023; Vassanadumrongdee & Matsuoka, 2005; Mariel et al., 2022).

Table 1. Factors associated with WTP for improving air quality and health impact prevention

	Variable	Scale	Description	Relations	References
Dependent Variables					
1	Binary WTP (likelihood of WTP)	Binary	1 if willing to pay some amount for atmospheric pollution reduction, 0 if not willing to pay any amount		Carlsson & Martinsson, 2001; Tantiwat & Gan, 2021
2	Numerical WTP (WTP amount)	Ratio Scale	The amount the respondent is willing to pay for atmospheric pollution mitigation.		Istamto et al., 2014; Khuc et al., 2022
Control Variables					
3	Gender	Binary	Sex of respondent (1 if male, 0 if female).	(+)	Guo et al., 2020; Filippini & Martínez-Cruz, 2016
4	Age	Ratio Scale	Age of respondent (years)	(+)	Hu & Liao, 2023; Huang et al., 2018; Vassanadumrongdee & Matsuoka, 2005
5	Income	Ratio Scale	Monthly income (THB)	(+)	Yoo et al., 2008; Shao et al., 2018; Wang et al., 2016
6	Expenditure	Ratio Scale	Respondent's monthly expenditure (THB)	(+)	Yoo et al., 2008; Wang & Zhang, 2009b; Courant & Porter, 1981
7	Education	Ordinal (dummy coded in regression)	1 if not completed school (base group), 2 if primary school, 3 if high school, 4 if vocational school, 5 if university degree	(+)	Hu & Liao, 2023; Vassanadumrongdee & Matsuoka, 2005; Mariel et al., 2022
8	Occupation	Categorical (dummy coded in regression)	1 if no job (base group), 2 if employee (government/ corporate), 3 if business owner, 4 if farmer, 5 if student or housewife	(+)	Wang et al., 2019; Li et al., 2024; Wang et al., 2016
9	Household headship	Binary	1 if respondent is a household head, 0 otherwise	(+)	Srisawasdi et al., 2021; Chigamba & Limuwa, 2021; Uma et al., 2020
Key Determinants Related Air Pollution					

	Variable	Scale	Description	Relations	References
10	Health condition	Binary	1 if the respondent is healthy, 0 otherwise	(-)	Hammitt & Zhou, 2006; Lee et al., 2011; Tang & Zhang, 2016
11	Perception: Sick of atmospheric pollution	Binary	1 if sick due to atmospheric pollution, 0 otherwise	(+)	Hammitt & Zhou, 2006; Wang et al., 2015b; Ortiz et al., 2009
12	Perception: Public electricity generation as pollution source	Binary	1 if the EGAT is perceived as a major source, 0 otherwise	(+)	Srisawasdi et al., 2021; Thanh & Lefevre, 2000, 2001
13	Perception: Biomass burning as pollution source	Binary	1 if biomass burning as a major source, 0 otherwise	(+)	Yang et al., 2018; Li et al., 2023; Zhao et al., 2018
14	Perception: Transportation as pollution source	Binary	1 if transportation as a major, 0 otherwise	(+)	Sánchez-garcía et al., 2021; Zahedi et al., 2019
15	Perception: Household as pollution source	Binary	1 if household activities as a major source, 0 otherwise	(+)	Wang & Mullahy, 2006; Freeman et al., 2019; Desaigues et al., 2011
16	Perception: Small factories as pollution source	Binary	1 if small factories as a major source, 0 otherwise	(+)	Sun et al., 2016; Ghanem et al., 2023; Zhang et al., 2019
17	Perception: Satisfaction with atmospheric quality	Binary	1 if satisfied with atmospheric quality, 0 otherwise	(-)	Luechinger, 2007; He & Zhang, 2021; Luechinger, 2009
18	Perception: Satisfaction with management of atmospheric quality	Binary	1 if satisfied with management of atmospheric quality by local authorities, 0 otherwise	(-)	Luechinger, 2007; Wei & Wu, 2017; Liu et al., 2016

2.3 Theoretical Framework of Contingent Valuation Method

Contingent Valuation Method (CVM) is grounded in Hanemann's (1984) Random Utility Theory, which posits that a respondent's utility can be divided into two components: the indirect utility function $V(p, q, m, s)$ and a stochastic error term (ε). Here, V represents the indirect utility derived from the consumption of goods and services, including environmental goods, given a person's income (m), environmental quality (q), socioeconomic characteristics (s), and the price of goods (p). The stochastic error term (ϵ) accounts for random, individual-specific factors that are not captured by the systematic components.

When air quality degraded from its current state (q^0) to a more polluted state (q^1), the utility of individual decreases from $U^0 = V(p, q^0, m, s)$ to $U^1 = V(p, q^1, m, s)$. This reduction in utility represents a loss in welfare for residents living in the affected area (Bateman et al., 2002; Chen et al., 2006; Y. Wang & Zhang, 2009). If air pollution levels exceed the standard and cause severe health effects, respondents' utility will decline, reflecting a decrease in their well-being and satisfaction. This deterioration could lead to health issues, reduced outdoor activities, and a general decline in quality of life (Cui et al., 2019). On the other hand, improved air quality can lead to better health outcomes, more opportunities for outdoor recreation, and a higher overall quality of life (Mostafanezhad, 2021; Saenz-de-Miera & Rosselló, 2014). If residents do not perceive any significant difference in air quality, their utility remains unchanged ($U^0 = U^1$), suggesting that the change in pollution levels is not significant enough to affect their daily lives or well-being.

To measure air pollution problems, the contingent valuation is applied to ask a resident a hypothetical question whether they are willing to pay t amount for an improvement in air quality or illness prevention. Their response would depend on how much they value health prevention. Specifically, if the amount they are willing to pay is greater than a specified amount ($WTP > t$), they will choose to pay. If WTP

$< t$, they will opt not to pay. This decision can be modelled using indirect utility functions, which represent the satisfaction or well-being the respondent derives from consuming goods and services, including environmental goods (Alberini et al., 1997; Bateman et al., 2002; Freeman, 1994).

According to Hanemann (1984), the intention was to depict the utility equivalence between two states: living with lower pollution (q^0) and a certain income (m), versus living with higher pollution (q^1) and adjusted income through compensation. Achieving a higher-quality environment requires payment from income (e.g., $m - t$), which aligns with the concept of WTP. Conversely, living with more pollution would warrant a compensation amount (e.g., $m + t$) based on willingness to accept (WTA), maintaining utility levels between these two choices.

For individuals preferring higher environmental quality with lower health impact (q^0), they would incur a cost, leading to a utility function expressed as $V(p, q^0, m - t, s)$. For those opting to accept pollution (q^1), they would receive compensation; thus, their utility would be $V(p, q^1, m + t, s)$. This scenario also introduces the concepts of compensating and equivalent surplus (Bateman et al., 2002). The compensating surplus is the income the resident is left after paying t for the air quality improvement by e amount, represented by $m - t$. Conversely, if the respondent is willing to accept payment t to tolerate a decline in air quality, their utility with income is represented by $m + t$, which is known as the equivalent surplus.

Thus, at the market equilibrium, where the respondent's utility remains constant despite a change in air quality and income, the indirect utility is

$$V(p, q^*, m, s) = V(p, q^* + e, m - t, s) \tag{1}$$

where q^* is the current air quality, e is the small improvement in air quality, and t is the amount paid for this improvement. Given that the air quality improvement and income change are at a minimum, we can approximate the change in utility

$V(p, q^* + e, m - t, s)$ using a first-order Taylor series expansion around (q^*, m), which allows us to express the utility as a function of small changes in air quality and income (Alberini et al., 1997; Yu & Abler, 2010).

$$V(p, q^* + e, m - t, s) \approx V(p, q^*, m, s) + \frac{\partial V(p,q^*,m,s)}{\partial q^*} e - \frac{\partial V(p,q^*,m,s)}{\partial m} t \tag{2}$$

where $\frac{\partial V(p,q^*,m,s)}{\partial q^*}$ is the marginal utility of air quality. $\frac{\partial V(p,q^*,m,s)}{\partial m}$ is the marginal utility of income. To derive WTP, we can set the utility functions from market equilibrium (1) equal to (2) and simplify:

$$V(p, q^*, m, s) = V(p, q^*, m, s) + \frac{\partial V(p,q^*,m,s)}{\partial q^*} e - \frac{\partial V(p,q^*,m,s)}{\partial m} t \tag{3}$$

$$0 = \frac{\partial V(p,q^*,m,s)}{\partial q^*} e - \frac{\partial V(p,q^*,m,s)}{\partial m} t \tag{4}$$

We find that the WTP (t) for air quality improvement can be expressed as:

$$WTP \ = t = \frac{\partial V(p,q^*,m,s)/\partial q^*}{\partial V(p,q^*,m,s)/\partial m} e \tag{5}$$

This expression tells us that WTP is proportional to the marginal utility of air quality relative to the marginal utility of income, essentially quantifying the trade-off that the respondent is willing to make between spending money and achieving better air quality with lower illness while keeping the utility constant. It quantifies how much the respondent values the improvement in air quality in monetary terms. Therefore, the WTP amount also implicitly includes the value of expected health benefits from improved air quality (Alberini et al., 1997). If a respondent is willing to pay, this amount represents the economic value they assign to those health improvements (Yu & Abler, 2010). By aggregating WTP across a population, we can estimate the total economic value of health benefits from reducing air pollution, making WTP a key measure of the economic value of mitigating its health effects (Hanemann, 1984; Mitchell & Carson, 2013; Randall et al., 1990; Seenprachawong, 2003; Wang & Zhang, 2009).

2.4 Derivation and Estimation of the Individual WTP

To estimate the individual WTP, Hanneman (1984) suggested an indirect utility function that is linear. The respondent has two states: state i (willing to pay) and state j (unwilling to pay). The indirect utility functions for these states are defined as:

$$V_i = \alpha + \beta(M - t) + \varepsilon_1 \tag{6}$$

$$V_j = \beta(M) + \varepsilon_0 \tag{7}$$

where V_i is the indirect utility in state i, where the budget is deducted by t, and utility is increased by α due to the air quality improvement. α represents the fixed-deterministic term or alternative-specific constant, which captures unobserved factors that affect utility but are not directly related to income or price to pay. These factors might include personal preferences, cultural influences, air quality improvement, or other subjective elements that are assumed to be different across individuals (Alberini et al., 1997; Bateman et al., 2002; Freeman, 1994). V_j is the indirect utility in state j (unwilling to pay) where utility remains unchanged. M is the income or budget. t is the willingness to pay to improve air quality. β is marginal utility of income or the parameters that determine the relationship between income, price, and utility. ε_0 and ε_1 is a random or stochastic term in each state capturing the individual-specific, unobserved factors that influence the utility, such as temporary changes in personal preferences, external influences, or mood; it is random in the sense that it reflects idiosyncratic variations (things that differ from person to person and from choice to choice). There is no α in (7) because it represents the utility of the "unwilling to pay" state, where the individual does not experience any change in air quality or other improvements.

To find WTP using the given indirect utility functions, we need to determine the change in price that would make the consumer indifferent between state 1 and state 0, given their utility levels. To do so, we set two indirect utility functions to be equal and solve for the change in price to pay:

$$\alpha + \beta(M - t) + \varepsilon_1 = \beta(M) + \varepsilon_0 \tag{8}$$

Assuming that $\varepsilon_1 - \varepsilon_0$ is a random variable with a mean of zero, then simplify the equation:

$$V_i(\alpha, M - t) = V_j(0, M) \tag{9}$$

Substituting the expressions for V_i and V_j from equations (8) and (9), we get:

$$\alpha + \beta(M - t) = \beta M \tag{10}$$

$$WTP = t = \frac{\alpha}{\beta} \tag{11}$$

The solution to this equation shows that the t (also known as WTP) is equal to the term α divided by the coefficient β.

Next, to define the suitable model for estimation, we need to consider the relationship between the indirect utility function and the distribution of stochastic error terms (Hanemann, 1984; Wang & Zhang, 2009). Assuming the probability of choosing state 1 (willing to pay), the probability function can be represented as:

$$Pr(yes) = \frac{1}{(1 + e^{-\Delta V})} \tag{12}$$

where ΔV represents the difference in the indirect utility between state 1 and state 0 ($-\Delta V = V_i - V_j$). When the stochastic error terms follow a standard normal distribution with a mean of zero and a variance of one, the Probit model should be utilized (Manning et al., 1999; Dickey & Fuller, 1979). The integral of the normal distribution would be used to estimate the probability that the individual is willing to pay based on the utility differences and the error terms (Mitchell & Carson, 2013). The probability given by the cumulative distribution function (CDF) of the normal distribution; the probabilities can be expressed as:

$$\Pr(yes) = \Pr(\varepsilon_{in} \leq V_{in} - V_{jn})$$

$$Pr\ (yes) = \int_{\varepsilon_n - \infty}^{V_{in}-V_{jn}} \frac{1}{\sqrt{2\pi\theta}} exp\left[-\frac{1}{2}(\frac{\varepsilon}{\sigma})^2\right] d\varepsilon$$

$$Pr(yes) = \frac{1}{\sqrt{2\pi\theta}} \int_{\varepsilon_n - \infty}^{V_{in}-V_{jn}} exp\left[-\frac{1}{2}u^2\right] du \quad (13)$$

where $\varepsilon_n - \infty$ is lower limit and u is a dummy variable. In this expression, the term $\frac{1}{\sqrt{2\pi\theta}} exp\left[-\frac{1}{2}u^2\right]$ represents the probability density function (PDF) of the standard normal distribution (Greene, 2008). The integral calculates the area under the PDF curve from $\varepsilon_n - \infty$ to $(V_{in} - V_{jn})$, which gives the probability to pay $Pr(yes)$. To integrate this PDF, which lacks a closed-form solution, numerical integration techniques or statistical software, such as NLOGIT, are used in this study.

Alternatively, the Logit model should be employed if the stochastic error terms, ε_{jn} and ε_{in} follow a logistic distribution (Dickey & Fuller, 1979). In the logit model, the probability that respondents are willing to pay $Pr(yes)$ is estimated using the logistic function (Albert & Chib, 1993; Papke, 1996), which is the inverse of the CDF of the logistic distribution. The probability of WTP, Pr(yes), in the logit model is written as:

$$Pr(yes) = \frac{1}{1+e^{-\mu(V_{in}-V_{jn})}} \quad (14)$$

where μ represents a parameter that determines the scale of the logistic distribution. To simplify, we substitute $X_{in} - X_{jn}$ for $V_{in} - V_{jn}$, yielding:

$$Pr(yes) = \frac{1}{1+e^{-\mu\left(X_{in}-X_{jn}\right)}} \quad (15)$$

Here, X_{in} and X_{jn} present the explanatory variables related to an individual's WTP. In the context of the Probit model, the probability is derived by integrating the PDF of the standard normal distribution over the range from $\varepsilon_n - \infty$ to $(V_{in} - V_{jn})$. The integral is:

$$\int_{\varepsilon_n - \infty}^{V_{in}-V_{jn}} \frac{1}{\sqrt{2\pi\theta}} exp\left[-\frac{1}{2}(\frac{\varepsilon}{\sigma})^2\right] d\varepsilon \quad (16)$$

We simplify the integral by substituting u = ε/σ:

$$\frac{1}{\sqrt{2\pi\theta}} \int_{\varepsilon_n - \infty}^{V_{in} - V_{jn}} exp\left[-\frac{1}{2}u^2\right] du \tag{17}$$

The integral represents Pr(yes), indicating the likelihood of an individual being willing to pay based on variations in stochastic error terms and differences in indirect utility. The probability can also be written as:

$$Pr(yes) = \frac{1}{1+e^{-\mu\left(V_{in} - V_{jn}\right)}} = \frac{1}{1+e^{-\mu(X_{in} - X_{jn})}} = \frac{e^{\beta'(\Delta X)}}{1+e^{\beta'(\Delta X))}} \tag{18}$$

This probability is derived from the logistic function, which transforms a linear combination of explanatory variables (or utility differences) into a probability ranging from 0 to 1. β is obtained through maximum likelihood estimation (MLE) of the model and reflects the effects of the explanatory variables *ΔX* on the likelihood of a positive outcome (Greene, 2008).

3. Research Methodology

The following sections detail the survey design and measurement of each key variable, starting with an overview of the survey design and bid structure, then how to calculate the WTP using double-bound CVM and open-ended CVM, followed by a description of the study site and the profile of respondents.

3.1 Survey Design

This study employed a face-to-face contingent valuation survey as detailed by Alberini et al. (1997) and Cummings and Taylor (1999). A random sample of 480 respondents from eight provinces, i.e., Chiang Mai, Chiang Rai, Phayao, Phrae, Nan, Mae Hong Son, Lampang, and Lamphun, was surveyed during the smog season (December 2023–May 2024), following the sample size determination methodology outlined by Yamane (1973). Participants were presented with a hypothetical scenario depicting the current state of air quality in the northern region alongside potential improvements under a proposed program. This scenario included a suggestion for a "Smog Mitigation Fund" initiated by the local government to finance water spray systems, protective kits, essential supplies, and financial assistance for those affected by pollution. To tackle the issue of incentive incompatibility as discussed in Bateman et al. (2002), where individuals' motivations may diverge from desired outcomes, and to mitigate potential hypothetical and cheap-talk biases, this study employed a combination of the double-bounded dichotomous choice (DBDC) format and the open-ended (OE) CVM, following the guidelines of Cummings and Taylor (1999). To mitigate incentive incompatibility, hypothetical bias, and cheap-talk bias, respondents were first shown visual aids depicting both current and improved air quality. Additionally, they were informed about the cheap-talk scripts before making their decisions on the contingent valuation questions.

3.2 Questionnaire

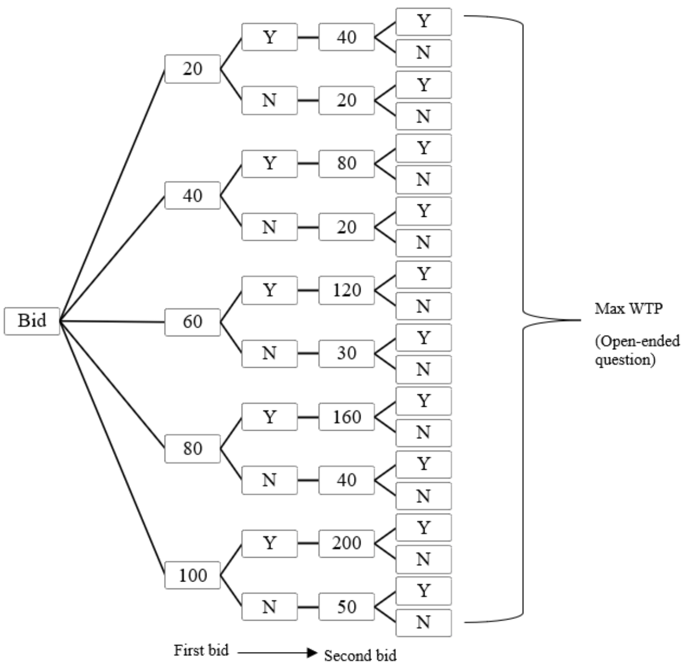
The questionnaire comprises four key sections. Part 1 assesses public understanding, attitudes, and perceptions regarding the haze situation in Northern Thailand, using a five-point Likert scale to evaluate perception, attitudes, and acknowledgment of PM2.5 pollution across sets of assessment, as suggested in Quintyne and Kelly (2023). Part 2 focuses on the perceived health effects of haze, as discussed in Alberini et al. (1997), with respondents indicating severity on a five-point Likert scale to represent their attitude toward perceived health effects. Part 3 employs the DBDC questions followed by the OE questions to measure WTP for a haze mitigation fund, where respondents evaluate their potential contributions in light of a hypothetical pollution scenario. Part 4 gathers socio-economic data, including gender, age, income, expenses, and education level, to explore how these factors influence perceptions and attitudes toward haze and air quality. To ensure the validity of the questionnaire, it underwent comprehensive content validity testing, pilot testing, and reliability analysis prior to data collection. Additionally, the study received approval from the Mae Fah Luang University Human Research Ethics

Committee (protocol number: EC23237-12), ensuring compliance with ethical standards in human research.

3.3 Payment Vehicle and Bid Structure

For payment vehicles, our survey utilized a one-time payment vehicle, allowing respondents to voluntarily donate a certain amount of income (per person per year) to a campaign aimed at improving air quality and preventing health damage caused by pollution, as followed in previous studies (Bateman et al., 2002; Cummings & Taylor, 1999; Mitchell & Carson, 2013). The bid structure (Figure 1) is designed by combining the DBDC question with the OE question to reduce potential bias and better reflect the actual WTP. In addition, the first bids (20,40,60,80,100) are determined based on results from a focus group of relevant stakeholders, including local policymakers, environmental researchers, and representatives from community organizations, to ensure that the bid amounts are realistic and appropriate for the target population, per Bateman et al. (2002) and Cummings and Taylor (1999).

Figure 1. Structure of the bids in CV study



Note: All amounts in THB at the 2024 exchange rate; U.S. $1 is equivalent to 35 THB.

3.4 Double-Bounded CVM Estimation

To derive WTP based on Double-Bounded CVM, the respondent is asked to pay a certain amount for their first bid (defined as B_0) if they are willing to pay. Then, the respondent is offered a second, higher (B_H) or lower (B_L) bid to double confirm their WTP. To simplify the probabilities for each response pattern (yes-yes, yes-no, no-yes, no-no) in terms of CDF, the possibility of choosing each response can be defined as:

$$Pr(yes_j, yes_j) = \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{0}\right)$$

$$Pr(yes_j, no_j) = \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{1j}\right) - \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{0}\right)$$

$$Pr(no_j, yes_j) = \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{n}\right) - \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{1j}\right)$$

$$Pr(no_j, no_j) = 1 - \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{0}\right) \quad (19)$$

The Log-likelihood function is subsequently defined as:

$$ln\, L(\alpha, \beta, \sigma, m, s, B) = \sum_{j=1}^{N}\left\{d_j^{1,1} ln\left[\Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{0}\right)\right] + d_j^{0,0} ln\left[1 - \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{0}\right)\right] + d_j^{0,1} ln\left[\Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{n}\right) - \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{1j}\right)\right] + d_j^{0,1} ln\left[\Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{1j}\right) - \Phi\left(\frac{\alpha}{\sigma}s_j - \frac{\beta}{\sigma}B_{2j}^{0}\right)\right]\right\} \quad (20)$$

where d is the set of dummy variables representing the dichotomous answer (yes or no) of respondent j (1= yes and 0 =no). Φ is the CDF of the standard normal distribution. s_j is socioeconomic variables (education) for respondent j. σ is standard deviation of the error term. β is a coefficient that measures the sensitivity of the respondent's utility to changes in the price or bid amount. α is a constant term or intercept representing the base level of utility when no other factors (like income or bid amounts) are considered. It captures any unobserved factors that might influence a respondent's WTP but are not accounted for explicitly in the model (Cameron & Quiggin, 1998). Then, we can apply the MLE to obtain the coefficients of this function and calculate the individual WTP.

3.5 Open-Ended CVM Estimation

After DBDC, we also use an OE question to ask the respondents to state their maximum WTP directly, without being given a set of predefined choices or bid amounts. In the context of contingent valuation, the OE question allows respondents to freely specify an amount they are willing to contribute to prevent illness from air pollution, offering flexibility and potentially more accurate reflections of their valuations (Mitchell & Carson, 2013). To derive the expected willingness to pay (E(WTP)) from OE responses, we typically use censored regression, e.g., the Tobit model, in cases where there is a censoring limit, and some respondents may have a WTP of zero. In this context, we use the Tobit model to understand how different factors influence individuals' WTP, as suggested by Mitchell and Carson (2013). The model allows us to assess the effect of variables like income and education, following Hoyos and Mariel (2010) and Mitchell and Carson (2013), on the natural log of WTP while accounting for cases where WTP is zero.

$$ln\,(WTP_i) \;= Z\beta + \varepsilon \tag{21}$$

where WTP_i is the stated willingness to pay of individual *i*. $Z\beta$ is the linear predictor (or deterministic part) influenced by socioeconomic factors like education and income ($Z\beta = \gamma\bar{S} + \delta\bar{Y} + \varepsilon$). γ is the coefficient for socioeconomic characteristics. $\bar{S}$ is an average socioeconomic characteristic, such as education level. δ is the coefficient for income. $\bar{Y}$ is an average income level of the respondent, and $\varepsilon \sim N(0, \sigma^2)$ is a normally distributed error term with mean zero and standard deviation σ^2.

According to Mitchell and Carson (2013), for cases where WTP>0, we calculate $E(WTP \mid WTP > 0)$, which involves two main components: the mean of the censored normal distribution $z\beta\Phi\left[\frac{Z}{\sigma}\beta\right]$ and the adjustment factor for censoring, represented by $\sigma\Phi\left[\frac{-Z}{\sigma}\beta\right]$. Using the properties of the normal distribution and integrating over the distribution where WTP>0, we get:

$$E(WTP \mid WTP > 0) = z\beta\Phi\left[\frac{Z}{\sigma}\beta\right] + \sigma\Phi\left[\frac{-Z}{\sigma}\beta\right] \quad (22)$$

where $\Phi\left[\frac{Z}{\sigma}\beta\right]$ is the CDF of the standard normal distribution, which gives the probability that a standard normal random variable is less than or equal to $\left[\frac{Z}{\sigma}\beta\right]$. Φ is the PDF of the standard normal distribution at $\left[\frac{Z}{\sigma}\beta\right]$. Then, we use NLOGIT to perform MLE to estimate the parameters of the Tobit model, allowing us to capture the mean WTP.

3.6 Factors Associated With Individual WTP

This study also delves into the factors affecting WTP to provide greater insight to policymakers. Multivariate logistic regression was employed to examine the association between respondents' social demographics and their WTP (per previous studies: Alberini et al., 1997; Brouwer et al., 2014; Liu et al., 2018). In logistic regression analysis, the outcome variable is typically binary, coded as 1 to indicate the willingness to pay and 0 to signify the unwillingness to pay. The empirical model for this objective is expressed as:

$$WTP_i = \beta_0 + \beta_1 B_i + \beta_2 S_i + \beta_3 C_i + \beta_4 P_i + \beta_5 U_i + \beta_6 I_i + \beta_7 Z_i + \varepsilon \quad (23)$$

where WTP_i is willingness to pay with the probability to say yes (P=1), B_i is the bid amount the respondent i is asked, and S_i represents socioeconomic characteristics, e.g., gender, education, and income of the respondent i, that are added as control variables and to avoid potential endogeneity bias. C_i represents the costs associated with illness prevention, e.g., air purifiers, facial masks, and related medical spending. P_i is the perception toward air pollution of the respondent i, U_i is the understanding toward air pollution of the respondent i, $I_i$is illness associated with the PM2.5 air pollution, Z_i is the dummy variable that is 1 if the respondent i lives in the pollution zone, β_i are coefficients of each variable, and ε is the random error. The descriptive statistics for each variable are presented in Table 2.

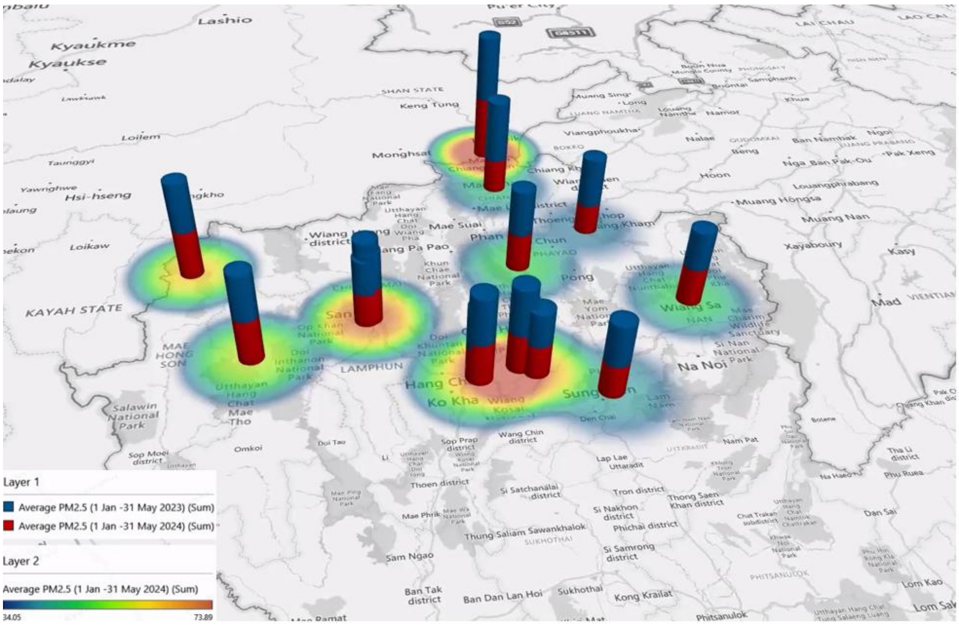
Table 2. Descriptive statistics of variables

Variable	n	Min	Max	Mean	SD
WTP	480	0	1	.44	.496
Gender	480	1	3	1.63	.529
Age	480	18	68	33	11.72
Education	480	6	20	17.51	2.155
Income	480	1	8	4.857	2.897
Pollution_Zone	480	1	8	4.00	2.413
Cost_Facemask	480	1	6	4.19	1.863
Cost_Medical	480	1	5	2.19	1.470
Cost_Airput	480	0	3	0.825	0.992
Understand	480	2	5	4.51	.431
Perception	480	1	5	3.89	1.047
Illness Severity	480	1	5	3.88	1.111

3.7 Study Site

The study focused on Northern Thailand, covering eight provinces: Chiang Mai, Lampang, Chiang Rai, Mae Hong Son, Nan, Lamphun, Phrae, and Phayao. This region consistently suffers from severe haze pollution between January and May each year. The haze, primarily resulting from agricultural burning, forest fires, and other pollution sources, leads to dangerous levels of PM2.5 particulate matter (Pollution Control Department of Thailand, 2023). From January 1 to May 31, 2023, these provinces experienced significant air pollution, with PM2.5 levels frequently surpassing the standard 24-hour threshold of 50 micrograms per cubic meter set by the Pollution Control Department of Thailand. Chiang Rai had the highest average PM2.5 level at 80.369 $\mu g/m^3$, followed by Nan (62.982 $\mu g/m^3$), Lampang (58.448 $\mu g/m^3$), Mae Hong Son (58.175 $\mu g/m^3$), Phayao (57.910 $\mu g/m^3$), Chiang Mai (53.756 $\mu g/m^3$), and Phrae (51.274 $\mu g/m^3$). Lamphun was the only province with an average PM2.5 level just below the standard at 49.901 $\mu g/m^3$.

Figure 2. Average PM2.5 24 hours in Northern region of Thailand (1 Jan–31 May 2023)



Source: Pollution Control Department of Thailand (2024).

Note: PM2.5 standard value, average 24 hours, is 50 micrograms/cubic meter. Air quality monitoring station: 35T Mueang District, Chiang Mai; 37T Mueang District, Lampang; 73T Mae Sai District, Chiang Rai; 58T Mueang District, Mae Hong Son; 67T Mueang District, Nan; 68T Mueang District, Lamphun; 69T Mueang District, Phrae; and 70T Mueang Phayao District, Phayao.

3.8 Respondents Profile

The descriptive statistics outline the socioeconomic profile of the 480 respondents in the study, providing insights into their gender, age, income, expenditure, education, and occupation. Of the respondents, 39.6% (190) are male, 58.1% (279) are female, and 2.3% (11) identify as alternative genders. The majority, 62.1%, are single and aged between 30 and 40 years. Most respondents earn a moderate monthly income ranging from 10,000 to 40,000 THB, with typical expenses of 300 to 400 THB for electricity and 100 to 200 THB for water.

Family sizes among the respondents vary, with the most common being four members (30.8%), followed by three members (22.3%) and five members (17.5%). Single-member households account for 6.5% of the sample. In terms of education, the majority have completed a bachelor's degree. The most common occupations are government employees or state workers (37.9%), followed by students (24.4%), private company employees (13.5%), and freelancers (9.4%). Geographically, respondents are predominantly from Chiang Mai, which has the highest representation with 96 individuals (20.0%), followed by Chiang Rai with 85 respondents (17.7%). Mae Hong Son has 54 respondents (11.3%), while other provinces include Phrae (52 respondents, 10.8%), Lampang (51 respondents, 10.6%), Phayao (48 respondents, 10.0%), and Nan and Lamphun with 47 respondents each (9.8%).

4. Findings

4.1 Perception Toward Health and Well-being Effects of Air Pollution

Table 3 summarizes the perception of 480 respondents toward the severity of health impacts from PM2.5 air pollution in Northern Thailand. Participants rated their attitude toward perceived symptoms on a scale of 1 (very low) to 5 (very high). The mean score indicates that most symptoms, such as eye irritation, headaches, runny nose, sore throat, dry cough, and asthma, are severe, reflecting discomfort and health impact. Even moderate symptoms like muscle pain and fever highlight the ongoing health risks. The overall mean score of 3.89 is within the severe range (3.41-4.20).

Table 3. Perception of health impact of air pollution by symptoms

No.	Symptoms	N	Min	Max	Mean	SD.	Opinion levels
1	Eye Irritation	480	1	5	4.45	0.811	Very High
2	Dry Cough	480	1	5	4.19	0.915	Very High
3	Sore Throat	480	1	5	4.12	0.917	Very High
4	Runny Nose	480	1	5	4.07	0.926	Very High
5	Strep Throat	480	1	5	4.07	1.015	Very High
6	Continuous Coughing	480	1	5	4.06	1.031	Very High
7	Allergies/Rashes	480	1	5	4.06	1.045	Very High
8	Asthma	480	1	5	3.96	1.113	Very High
9	Shortness of Breath	480	1	5	3.93	1.072	Very High
10	Wheezing	480	1	5	3.88	1.11	Very High

No.	Symptoms	N	Min	Max	Mean	SD.	Opinion levels
11	Bronchitis	480	1	5	3.78	1.257	Very High
12	Headache	480	1	5	3.75	0.992	Very High
13	Chest Pain/Pressure	480	1	5	3.62	1.142	Very High
14	Have A Fever	480	1	5	3.24	1.211	Moderate
15	Muscle Pain	480	1	5	3.19	1.18	Moderate

Note: The scoring criteria for average opinion levels is interpreted based on the following ranges: 1.00–1.80 = Very low symptoms (none); 1.81–2.60 = Low symptom (Mild); 2.61–3.40 = Moderate symptom; 3.41–4.20 = High symptom (severe); 4.21–5.00 = Very high symptom (Most Severe).

Our findings are consistent with previous studies that emphasize the severe impact of air pollution on public health, particularly respiratory symptoms. For instance, Vichit-Vadakan and Vajanapoom (2011) conducted research in Bangkok and Thailand's industrial zones, demonstrating a strong link between pollution levels and respiratory issues. Similarly, Alberini et al. (1997) found comparable effects in Taiwan, highlighting the increased risk of both chronic and acute respiratory conditions. These studies, along with our analysis, underscore the critical need for effective measures to mitigate air pollution and protect public health.

4.2 Public Understanding of the Air Pollution in Northern Thailand

This section assesses public understanding of PM2.5 air pollution in Northern Thailand during 2023–2024, covering sources, health impacts, preventive measures, and mask effectiveness. It evaluates knowledge of air pollution risks, especially during outdoor exercise, the vulnerability of certain groups, like pregnant women, the benefits of public transportation, and the importance of following safety guidelines during high pollution. Each question was administered through face-to-face interviews aimed at ensuring that respondents fully comprehended the questions before providing their ratings.

The results summarize ten assessments (KNW1 to KNW10), as previously applied in Quintyne and Kelly (2023), covering the following key points: forest burning as the main source of PM2.5, avoiding outdoor exercise during high pollution, PM2.5's impact on the respiratory system, long-term effects like blood vessel sedimentation and heart attack risks, and the threat to pregnant women and fetuses. They also include the benefits of public transportation, mask reuse, N95 masks' superior filtration for particles under 0.3 microns, handling high dust levels, and the danger of PM2.5 levels between 100–500 μg/m³ for daily life and outdoor activities.

Table 4. Public understanding of air pollution in Northern Thailand

Assessment	**n**	**Min**	**Max**	**Mean**	**SD**	**Level**
1. Forest burning & factory emissions cause PM2.5.	480	1	5	4.46	.803	Very high
2. Avoid outdoor exercise during high pollution.	480	2	5	4.69	.595	Very high
3. PM2.5 harms the respiratory system.	480	1	5	4.82	.481	Very high
4. Long-term exposure can lead to heart attacks.	480	2	5	4.55	.676	Very high
5. PM2.5 threatens pregnant women and fetuses.	480	1	5	4.59	.675	Very high
6. Public transport reduces air pollution.	480	1	5	4.00	.981	High
7. Don't reuse face masks.	480	1	5	4.66	.686	Very high
8. N95 masks filter better than regular masks.	480	1	5	4.54	.661	Very high
9. You know how to manage health impact.	480	1	5	4.15	.838	High
10. PM2.5 levels above 100 μg/m³ are unsafe.	480	1	5	4.61	.669	Very high
Average	**480**	**1**	**5**	**4.51**	**.706**	**Very high**

Note: The scoring criteria for average opinion levels is interpreted based on the following ranges: 1.00–1.80 = Very low understanding; 1.81–2.60 = Low understanding; 2.61–3.40 = Moderate understanding; 3.41–4.20 = High understanding; 4.21–5.00 = Very high understanding.

4.3 Distribution of WTP From Double-Bounded CVM Question

Table 5 presents the results of individual WTP and the distribution of answers from DBDC questions among 480 respondents. This result highlights that lower bid amounts (such as in Bid Version i) tend to generate more "Yes/Yes" and "Yes/No" responses, while higher bid amounts lead to more "No/Yes" and "No/No" responses. This pattern aligns with expected behavior in a double-bounded discrete choice experiment, where respondents are more likely to agree to lower prices and less likely to accept higher prices (Akhtar et al., 2017; Chen et al., 2006; Hammitt & Zhou, 2006b; Hanemann, 1984; Mitchell & Carson, 2013).

Table 5. Distribution of WTP response for the double-bounded discrete choice (n=480)

Bid Version	Bid Amount (THB)			Distribution of WTP Response				No. of Responses
	First Bid	Second Bid		Yes/Yes	Yes/No	No/Yes	No/No	
		Lower	Upper					
i	20	10	40	78(16.25)	49(10.20)	8(1.67)	22(4.58)	157(32.71)
ii	40	20	80	55(11.46)	40(8.33)	2(0.42)	33(6.88)	130(27.08)
iii	60	30	120	41(8.54)	31(6.46)	5(1.04)	21(4.38)	98(20.42)
iv	80	40	160	24(5.00)	13(2.71)	1(0.21)	14(2.92)	52(10.83)
v	100	50	200	11(2.29)	11(2.29)	5(1.04)	16(3.33)	43(8.96)
			Total	209(43.54)	144(30)	21(4.38)	106(22.08)	480(100)

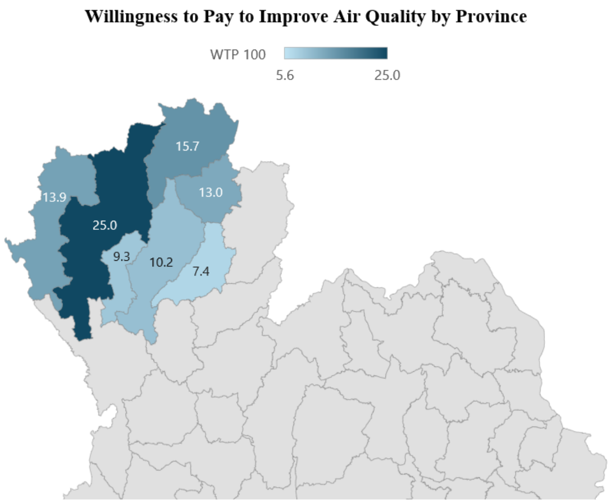
Note: Unit: Person (Percent).

The survey results indicate that 22.08% of respondents are unwilling to pay, with various reasons underlying their decision. The most common reason (11.5%) is the belief that addressing the smog problem is the government's responsibility, while 9.0% lack trust in the effectiveness of a donation-based solution. Additionally, 2.9% cite financial constraints but express TWP if their income improves. A small fraction (0.4%) considers the issue unimportant, and 1.9% provide other reasons, including skepticism about the causes of forest fires, the role of the state in funding solutions, and doubts about the impact of individual contributions.

Regional Variation of WTP

Figure 3 illustrates the WTP to prevent illness by province, expressed as a percentage of respondents who are willing to pay. The highest percentage of respondents willing to pay is in Chiang Mai, where 25.0% of the population is willing to invest in better air quality. Following Chiang Mai, 15.7% of respondents in Chiang Rai and 13.9% in Mae Hong Son are willing to pay. In Phayao, 13.0% of the population is willing to contribute, while in Lampang, this figure is 10.2%. Lamphun has a willingness to pay of 9.3%, and Phrae stands at 7.4%. The lowest percentage is in Nan, where only 5.6% of respondents are willing to pay for improved air quality. The map uses varying shades of blue to visually represent these percentages, with darker shades indicating higher WTP and lighter shades indicating lower WTPs.

Figure 3. Willingness to pay to prevent illness by province



Note: The values displayed on the map represent the percentage of respondents willing to pay 100 THB per person per year to prevent illness in Northern Thailand, based on a survey conducted from January to May 2024.

4.4 Estimated WTP Using Double-Bounded CVM

This section presents the estimated individual WTP based on two methods of asking respondents. Table 6 shows the results derived from the DBDC question, where the respondent is asked about an initial bid of donation to an air mitigation fund, followed by a second but higher or lower bid to confirm their WTP. We obtain WTP parameters for equation (11) by maximizing the log-likelihood function shown in equation (20), using NLOGIT software, which is commonly used for estimating econometric models. The maximum likelihood estimated results are shown in Table 6.

Table 6. Estimated WTP based on double-bounded dichotomous choice question

Estimated Parameters	Probit Model			Logit Model		
	(1)	(2)	(3)	(4)	(5)	(6)
pha,bta; start	0.001	0.01	0.1	0.001	0.01	0.1
Marginal utility of air quality (α)	1.981*** (0.057)	1.630*** (0.372)	1.763*** (0.639)	8.935*** (0.566)	4.5104*** (0.2781)	11.269*** (0.570)
Marginal utility of income (β)	0.184*** (0.001)	0.184*** (0.268)	0.185*** (0.001)	0.224*** (0.566)	0.442*** (0.007)	0.232*** (0.570)

Log likelihood function	-610385.3	-610386.2	-610391.2	-693959.41	-531111.51	-693959.4
Info. Criterion: AIC	2527.984	2537.988	2538.009	2885.486	2538.168	2885.486
WTP (THB/Year)	**107.40**	**90.00**	**97.93**	**39.92**	**10.21**	**48.63**
Fraction of income (%)	**0.458**	**0.383**	**0.413**	**0.170**	**0.044**	**0.207**

Note: The likelihood function includes bid amounts (bid, bidhi, bidlow), response indicators (yy, yn, ny, nn), and estimated parameters α (alpha) and β (bta) to model WTP using a probit-based approach. Other relevant factors are either held constant or captured within the error term (Yu & Abler, 2010). *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

4.5 Estimated WTP Using Open-Ended CVM

WTP based on the OE question reveals considerable variability among respondents in their willingness to improve the air quality and prevent illness. While 151 individuals are unwilling to pay, 329 individuals are willing to contribute substantial amounts, with the highest value reaching 10,000 THB. The most common WTP value is 100 THB, with 108 respondents (30.9%) willing to pay this amount. This is followed by 500 THB, with 42 respondents (12.0%) indicating their WTP this amount. The average WTP of 354.17 THB (per person per year) suggests that, overall, respondents are moderately willing to support air quality initiatives. However, the high standard deviation (SD = 915) indicates significant diversity in responses, likely reflecting differences in income, environmental concern, and perceived effectiveness of air quality policies. The distribution of WTP from open-ended CVM is shown in Table 7.

Table 7. Willingness to pay collected from the open-ended question

WTP (THB)	Frequency	Percent	Valid Percent	Cumulative Percent
0	20	4.2	5.7	5.7
1	5	1	1.4	7.2
5	1	0.2	0.3	7.4
10	7	1.5	2	9.5
12	1	0.2	0.3	9.7
19	1	0.2	0.3	10
20	24	5	6.9	16.9
30	5	1	1.4	18.3
40	15	3.1	4.3	22.6

WTP (THB)	Frequency	Percent	Valid Percent	Cumulative Percent
50	21	4.4	6	28.7
60	4	0.8	1.1	29.8
80	3	0.6	0.9	30.7
100	108	22.5	30.9	61.6
120	1	0.2	0.3	61.9
150	6	1.3	1.7	63.6
160	1	0.2	0.3	63.9
200	29	6	8.3	72.2
240	1	0.2	0.3	72.5
250	1	0.2	0.3	72.8
300	13	2.7	3.7	76.5
360	1	0.2	0.3	76.8
400	2	0.4	0.6	77.4
500	42	8.8	12	89.4
600	3	0.6	0.9	90.3
720	1	0.2	0.3	90.5
1,000	24	5	6.9	97.4
1,800	1	0.2	0.3	97.7
2,000	2	0.4	0.6	98.3
3,000	2	0.4	0.6	98.9
5,000	1	0.2	0.3	99.1
6,000	1	0.2	0.3	99.4
10,000	2	0.4	0.6	100
Total	**480**			

In addition, we also use the OE CVM method to calculate the average individual WTP following equation (21) and previous studies (Bateman et al., 2002; Yu & Abler, 2010). Estimated results from the censored regression model (Tobit model) are shown in Table 8. The constant is -462.051 with a standard error of 393.677. The coefficients for education and income are 24.989 and 0.0008, respectively, with standard errors of 22.558 and 0.001, respectively. The disturbance standard deviation (Sigma) is 999.707. The means of education and income are 15.348 years and 23461 THB/month.

Table 8. Estimated results of the Tobit Model

Variable	**Coefficient**	**Std.**	**b/St.Er.**	**P[|z|>z]**	**Mean**
Primary Index Equation for Model					
Constant	-462.051	393.677	-1.174	0.240	
INC	0.0008	0.001	0.783	0.433	23461.03
EDU	24.989	22.558	1.108	0.268	15.348
Disturbance		*standard*		*deviation*	
Sigma (σ)	999.707	40.005	24.990	0.000	
E(WTP)	**368.964**				

Note: The independent variable is ln(WTP) collected by an open-ended question. The decision to include only education and income in the model is based on both theoretical and practical considerations. These two variables are widely recognized as key demand shifters in WTP models, as income reflects an individual's financial capacity to contribute, while education often correlates with awareness and perception of air pollution issues.

To calculate the average willingness to pay (E(WTP)), we incorporate the income and other socioeconomic variables (education) as key variables to derive the WTP, as suggested in Hoyos and Mariel (2010) and Mitchell and Carson (2013). Mathematically, we use equation (22):

$$E(WTP \mid WTP > 0) = z\beta\Phi\left[\frac{Z}{\sigma}\beta\right] + \sigma\Phi\left[\frac{-Z}{\sigma}\beta\right]$$

Given the value of $z\beta = -462.05 + 24.989(\overline{edu}) + 0.0008(\overline{inc})$, we substitute the mean of education (15.348) and income (23461.03) (which are the sample means from our survey), resulting in $z\beta$ = -60.164. Next, we standardize by the standard deviation of the disturbance term: $z\beta/\sigma = -60.164/999.707$ = -0.06. Then, we find Φ(−0.06) = 0.477, and Φ(0.06) = 0.398. These probabilities are then used in equation (23) to calculate the expected willingness to pay (E(WTP)) as

$$E(WTP) = z\beta\Phi\left[\frac{Z}{\sigma}\beta\right] + \sigma\Phi\left[\frac{-Z}{\sigma}\beta\right]$$

$$= -60.164\,[0.477] + 999.707\,[0.398]$$

$$= 368.964 \text{ THB/ person/year}$$

The E(WTP) for air quality improvement is 368.964 THB per person per year, about 10.28 USD (with 35 THB = 1 USD), or 1.57% of the average annual income (0.18% of the GDP per capita in 2023). For a household of four, this equates to approximately 1,475 THB or 41.12 USD annually.

Previous research, such as Vassanadumrongdee et al. (2004), used meta-analysis to estimate the annual cost of mortality from air pollution in Thailand, finding it ranged from 0.74 to 1.32 million USD. Additionally, Tantiwat et al. (2021) quantified the economic benefits of air quality improvements in Bangkok at approximately 18.8 billion THB per year, reflecting the substantial economic burden of air pollution. Our finding contributes to a deeper understanding of the health effects of air pollution based on individual preferences.

To contextualize our findings, we compare them with individual WTP estimates from other countries. For instance, a study in the United Kingdom found that individuals are willing to pay approximately \$130 (0.27% of the GDP per capita) annually in taxes to reduce nitrogen dioxide (NO_2) levels by 1 $\mu g/m^3$ (Leicester & Stoye, 2023). Similarly, research in China reported that urban residents are willing to pay about 1.42% of the GDP per capita for marginal reductions in air pollution (Wang & Zhang, 2022). These comparisons suggest that the WTP in Thailand is relatively modest, potentially reflecting differences in economic capacity and public awareness. Our findings also align with Phairuang et al. (2017), who emphasized the significant impact of agricultural activities, forest fires, and agro-industries on air quality in Thailand. This underscores the necessity for collective efforts and regional cooperation to effectively address air pollution challenges in the country.

4.6 Factors Affecting WTP to Prevent Health Impact

Table A1 presents the descriptive statistics of all variables. Table 9 presents the estimated results of the Binary Logistic Regression. Our findings include a significant negative effect of the initial bid on WTP, which suggests the presence of starting point bias; higher initial bids correspond to a reduced likelihood of WTP (Bateman et al., 2002; Ladenburg & Olsen, 2008). Gender and age are also significant predictors, with males and older individuals less likely to demonstrate WTP. In contrast, higher income is positively associated with WTP, indicating that wealthier individuals are more inclined to contribute financially to air quality improvements. Furthermore, the costs associated with air purifiers and facemasks are positively correlated with WTP, implying that individuals who recognize the expense of these protective measures are more likely to pay for improved air quality. Perception and acknowledgment of air quality issues are marginally significant and positively influence WTP, underscoring the role of environmental awareness. However, variables such as education, medical costs, understanding of air pollution, residing in a pollution zone, and perceived health impact severity do not exhibit a significant impact on WTP. Overall, both Probit and Logit models yield consistent results, highlighting the robustness of the findings. These insights emphasize the importance of socioeconomic factors and environmental awareness in shaping public willingness to invest in air quality improvements.

Table 9. Factors associated with WTP

Variable	**[1] Probit**		**[2] Logit Model**	
	Coefficient	**Prob.**	**Coefficient**	**Prob.**
Initial Bid	-0.005**	0.046	-0.008**	0.044
Gender	-0.221*	0.066	-0.359*	0.068
Age	-0.153***	0.009	-0.247**	0.011
Education	-0.115	0.233	-0.190	0.228
Income	0.444**	0.032	0.716**	0.036
Cost_Airpur	0.142**	0.049	0.230**	0.050
Cost_Facemask	0.075**	0.048	0.122**	0.050
Cost_Medical	-0.058	0.238	-0.093	0.248
Perception	0.563*	0.088	0.915*	0.092
Understand	-0.245	0.339	-0.387	0.354
Pollution_Zone	-0.041	0.122	-0.063	0.138
Illness	0.039	0.653	0.065	0.640

Variable	[1] Probit		[2] Logit Model	
	Coefficient	Prob.	Coefficient	Prob.
C	-2.341	0.019	-3.836	0.020
Log likelihood	-280.73		-280.815	
Akaike info criterion	1.335		1.336	
Schwarz criterion	1.456		1.456	
Hannan-Quinn criterion	1.382		1.383	
McFadden R-squared	0.071		0.700	

Note: Dependent variable is the probability of WTP in dichotomous questions. Estimation is based on the Newton-Raphson / Marquardt steps binary method. *** p<0.01, ** p<0.05, and * p<0.1.

5. Conclusion and Policy Implications

The study delves into the WTP for air illness prevention and for air quality improvement. The survey reveals that 73.8% of respondents are willing to pay to prevent illness from PM2.5 pollution. The main reasons include the importance of addressing pollution (37.1%), the belief that solving smog issues requires collective action (22.1%), and individual financial capacity (8.5%). Smaller groups cited confidence in fund effectiveness (3.8%) or expressed concerns about the government's commitment to tackling the problem (2.3%). Factors influencing WTP, analyzed through a multivariate logistics regression model, include age, gender, income, education, cost associated with illness prevention, awareness of air pollution issues, and perceived health risks. The results indicate that higher income, higher education, and greater perceived health risks significantly determine WTP, with higher-income individuals and those with higher educational attainment more likely to express a higher WTP. The mean WTP to prevent illness, based on OE CVM, is estimated at 368.964 THB (approximately USD 11) per person per year. The double-bounded dichotomous choice analysis estimates annual WTP across both probit and logit models. WTP values range from 10.21 to 107.40 THB/year, with respondents willing to allocate a modest income fraction (0.04% to 0.46%) to prevent illness associated with PM2.5 air pollution. This WTP underscores the value residents place in improving air quality and mitigating the adverse effects of air pollution on their health and well-being. The study also reveals significant regional variation in WTP across the seven provinces. Chiang Mai has the highest mean WTP at 1,800 THB per household per year, followed by Chiang Rai and Phayao with mean WTPs of 1,600 THB and 1,500 THB, respectively. In contrast, Lamphun has the lowest mean WTP at 1,200 THB per household per year. This variation reflects differences in income levels, awareness of air pollution issues, and perceived health risks across the provinces.

These findings provide valuable insights for policy actions to effectively address air pollution in Northern Thailand. Establishing a regional smog mitigation fund could serve as a critical financial tool, supporting initiatives such as public air purification systems in schools and public areas, household subsidies for air purifiers, green infrastructure projects, and research and development focused on reducing PM2.5 emissions. In addition, providing targeted subsidies for air purifiers and healthcare cost relief would alleviate the financial burden on households affected by poor air quality.

6. Limitations

The limitation of this study is the potential for anchoring bias in the survey method. By presenting respondents with an initial bid amount, their responses may be influenced by this figure, leading them to report a WTP closer to the suggested amount rather than reflecting their true preferences. Future research could address this limitation by asking respondents to provide their WTP amount before presenting any dichotomous questions, or by using randomized treatments to reduce the influence of anchoring. In addition, estimated coefficients for OE CVM may be biased due to the omission of relevant control variables. Key factors such as environmental awareness and proximity to pollution sources were not included in the analysis, which could influence individuals' willingness to pay. Future research could incorporate these variables to better capture the full range of factors affecting WTP and improve the robustness of the model.

Acknowledgments

This research was funded by Mae Fah Luang University (Contract no. 671A12021). The authors also appreciate the invaluable support from the Sustainability and Entrepreneurship Research Center (SERC), Mae Fah Luang University, and acknowledge the insightful comments from the reviewers and editors, which helped enhance the quality of this work.

References

Abidin, A. U., Maziya, F. B., Susetyo, S. H., Yoneda, M., & Matsui, Y. (2023). Exposure particulate matter (PM2.5) and health risk assessment on informal workers in landfill site, Indonesia. *Environmental Challenges*, *13*. https://doi.org/10.1016/j.envc.2023.100795

Ain, Q., Ullah, R., Kamran, M. A., & Zulfiqar, F. (2021). Air pollution and its economic impacts at household level: Willingness to pay for environmental services in Pakistan. *Environmental Science and Pollution Research*, *28*(6). https://doi.org/10.1007/s11356-020-11023-4

Akhtar, S., Saleem, W., Nadeem, V. M., Shahid, I., & Ikram, A. (2017). Assessment of willingness to pay for improved air quality using contingent valuation method. *Global Journal of Environmental Science and Management*, *3*(3). https://doi.org/10.22034/gjesm.2017.03.03.005

Alberini, A., Cropper, M., Fu, T. T., Krupnick, A., Liu, J. T., Shaw, D., & Harrington, W. (1997). Valuing health effects of air pollution in developing countries: The case of Taiwan. *Journal of Environmental Economics and Management*, *34*(2). https://doi.org/10.1006/jeem.1997.1007

Albert, J. H., & Chib, S. (1993). Bayesian analysis of binary and polychotomous response data. *Journal of the American Statistical Association*, *88*(422). https://doi.org/10.1080/01621459.1993.10476321

Almetwally, A. A., Bin-Jumah, M., & Allam, A. (2020). Ambient air pollution and its influence on human health and welfare: an overview. *Environmental Science and Pollution Research*, *27*, 24815–24830. https://doi.org/10.1007/s11356-020-09042-2

Bateman, I., Carson, R., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., & Loomes, G. (2002). *Economic Valuation with Stated Preference Techniques*. Edward Elgar Publishing.

Bergstra, A. D., Brunekreef, B., & Burdorf, A. (2018). The effect of industry-related air pollution on lung function and respiratory symptoms in school children. *Environmental Health: A Global Access Science Source*, *17*(1). https://doi.org/10.1186/s12940-018-0373-2

Bernstein, J. A., Alexis, N., Barnes, C., Bernstein, I. L., Bernstein, J. A., Nel, A., Peden, D., Diaz-Sanchez, D., Tarlo, S. M., & Williams, P. B. (2004). Health effects of air pollution. *Journal of Allergy and Clinical Immunology*, *114*(5), 1116–1123. https://doi.org/10.1016/j.jaci.2004.08.030

Brouwer, R., Tinh, B. D., Tuan, T. H., Magnussen, K., & Navrud, S. (2014). Modeling demand for catastrophic flood risk insurance in coastal zones in Vietnam using choice experiments. *Environment and Development Economics*, *19*(2). https://doi.org/10.1017/S1355770X13000405

Cameron, T. A., & Quiggin, J. (1998). Estimation using contingent valuation data from a “dichotomous choice with follow-up” questionnaire: Reply. *Journal of Environmental Economics and Management*, *35*(2). https://doi.org/10.1006/jeem.1998.1026

Carlsson, F., & Johansson-Stenman, O. (2000). Willingness to pay for improved air quality in Sweden. *Applied Economics*, *32*(6). https://doi.org/10.1080/000368400322273

Carlsson, F., & Martinsson, P. (2001). Willingness to pay for reduction in air pollution: A multilevel analysis. *Environmental Economics and Policy Studies*, *4*, 17–27.

Chen, L., Ouyang, Z. Y., Wang, X. K., Miao, H., & Duan, X. N. (2006). Applications of contingent valuation method in evaluation of non-market values. *Acta Ecologica Sinica*, *26*(2).

Chigamba, G., & Limuwa, M. (2021). Does paying for aquatic resources matter? A case of an African riverine ecosystem. *Sustainability*, *13*(8), 1–13.

Courant, P. N., & Porter, R. C. (1981). Averting expenditure and the cost of pollution. *Journal of Environmental Economics and Management*, *8*(4), 321–329. https://doi.org/https://doi.org/10.1016/0095-0696(81)90044-9

Cui, C., Wang, Z., He, P., Yuan, S., Niu, B., Kang, P., & Kang, C. (2019). Escaping from pollution: The effect of air quality on inter-city population mobility in China. *Environmental Research Letters*, *14*. https://doi.org/10.1088/1748-9326/ab5039

Cummings, R. G., & Taylor, L. O. (1999). Unbiased value estimates for environmental goods: A cheap talk design for the contingent valuation method. *American Economic Review*, *89*(3). https://doi.org/10.1257/aer.89.3.649

Delucchi, M. A., Murphy, J. J., & McCubbin, D. R. (2002). The health and visibility cost of air pollution: A comparison of estimation methods. *Journal of Environmental Management*, *64*(2). https://doi.org/10.1006/jema.2001.0515

Desaigues, B., Ami, D., Bartczak, A., Braun-Kohlová, M., Chilton, S., Czajkowski, M., Farreras, V., Hunt, A., Hutchison, M., Jeanrenaud, C., Kaderjak, P., Máca, V., Markiewicz, O., Markowska, A., Metcalf, H., Navrud, S., Nielsen, J. S., Ortiz, R., Pellegrini, S., … Urban, J. (2011). Economic valuation of air pollution mortality: A 9-country contingent valuation survey of value of a life year (VOLY). *Ecological Indicators*, *11*(3), 902–910. https://doi.org/https://doi.org/10.1016/j.ecolind.2010.12.006

Diallo, S. M., & Seck, A. (2023). Air pollution in urban Africa: Understanding attitudes and economic valuation in the case of Dakar, Senegal. *Sustainability (Switzerland)*, *15*(2). https://doi.org/10.3390/su15021494

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366). https://doi.org/10.1080/01621459.1979.10482531

Donfouet, H. P. P., Cook, J., & Jeanty, P. W. (2015). The economic value of improved air quality in urban Africa: A contingent valuation survey in Douala, Cameroon. *Environment and Development Economics*, *20*(5). https://doi.org/10.1017/S1355770X14000552

Dong, D., Xu, B., Shen, N., & He, Q. (2021). The adverse impact of air pollution on China's economic growth. *Sustainability (Switzerland)*, *13*(16). https://doi.org/10.3390/su13169056

Filippini, M., & Martínez-Cruz, A. L. (2016). Impact of environmental and social attitudes, and family concerns on willingness to pay for improved air quality: A contingent valuation application in Mexico City. *Latin American Economic Review*, *25*(1), 7. https://doi.org/10.1007/s40503-016-0037-y

Freeman, A. M. (1994). *The measurement of environmental and resource values: Theory and methods*. New York: Routledge.

Freeman, R., Liang, W., Song, R., & Timmins, C. (2019). Willingness to pay for clean air in China. *Journal of Environmental Economics and Management*, *94*, 188–216. https://doi.org/https://doi.org/10.1016/j.jeem.2019.01.005

Ghanem, S., Ferrini, S., & Di Maria, C. (2023). Air pollution and willingness to pay for health risk reductions in Egypt: A contingent valuation survey of Greater Cairo and Alexandria households. *World Development*, *172*, 106373. https://doi.org/https://doi.org/10.1016/j.worlddev.2023.106373

Greene, W. H. (2008). The econometric approach to efficiency analysis. In H. O. Fried (ed.) *The measurement of productive efficiency and productivity change*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195183528.003.0002

Guo, D., Wang, A., & Zhang, A. T. (2020). Pollution exposure and willingness to pay for clean air in urban China. *Journal of Environmental Management*, *261*, 110174. https://doi.org/https://doi.org/10.1016/j.jenvman.2020.110174

Halvorsen, B. (1996). Ordering effects in contingent valuation surveys: Willingness to pay for reduced health damage from air pollution. *Environmental and Resource Economics*, *8*(4). https://doi.org/10.1007/BF00357416

Hammitt, J. K., & Zhou, Y. (2006). The economic value of air-pollution-related health risks in China: A contingent valuation study. *Environmental and Resource Economics*, *33*, 399–423. https://doi.org/10.1007/s10640-005-3606-0

Hanemann, W. M. (1984). Welfare evaluations in contingent valuation experiments with discrete responses. *American Journal of Agricultural Economics*, *66*(3). https://doi.org/10.2307/1240800

He, J., & Zhang, B. (2021). Current air pollution and willingness to pay for better air quality: Revisiting the temporal reliability of the contingent valuation method. *Environmental and Resource Economics*, *79*(1), 135–168. https://doi.org/10.1007/s10640-021-00556-y

Hoyos, D., & Mariel, P. (2010). Contingent valuation: Past, present and future. *Prague Economic Papers*, *4*. https://doi.org/10.18267/j.pep.380

Hu, L., & Liao, W. (2023). Is there a stronger willingness to pay for air quality improvement with high education: new evidence from a survey in China. *Environmental Science and Pollution Research*, 28990–29014. https://doi.org/10.1007/s11356-022-24108-z

Huang, D., Andersson, H., & Zhang, S. (2018). Willingness to pay to reduce health risks related to air quality: evidence from a choice experiment survey in Beijing. *Journal of Environmental Planning and Management*, *61*(12), 2207–2229. https://doi.org/10.1080/09640568.2017.1389701

Istamto, T., Houthuijs, D., & Lebret, E. (2014). Willingness to pay to avoid health risks from road-traffic-related air pollution and noise across five countries. *Science of The Total Environment*, 497–498, 420–429. https://doi.org/https://doi.org/10.1016/j.scitotenv.2014.07.110

Khuc, Q. Van, Nong, D., & Phu Vu, T. (2022). To pay or not to pay that is the question - for air pollution mitigation in a world's dynamic city: An experiment in Hanoi, Vietnam. *Economic Analysis and Policy*, *74*, 687–701. https://doi.org/https://doi.org/10.1016/j.eap.2022.03.023

Kurt, O., Zhang, J., & Pinkerton, K. (2016). Pulmonary health effects of air pollution. *Current Opinion in Pulmonary Medicine*, *22*, 138. https://doi.org/10.1097/MCP.0000000000000248

Ladenburg, J., & Olsen, S. B. (2008). Gender-specific starting point bias in choice experiments: Evidence from an empirical study. *Journal of Environmental Economics and Management*, *56*(3). https://doi.org/10.1016/j.jeem.2008.01.004

Lee, Y. J., Lim, Y. W., Yang, J. Y., Kim, C. S., Shin, Y. C., & Shin, D. C. (2011). Evaluating the PM damage cost due to urban air pollution and vehicle emissions in Seoul, Korea. *Journal of Environmental Management*, *92*(3), 603–609. https://doi.org/https://doi.org/10.1016/j.jenvman.2010.09.028

Leicester, A., & Stoye, G. (2023). Estimating the public's willingness to pay for air quality improvements: Evidence from the UK. *Journal of Environmental Economics and Management*, *105*, 102395. https://doi.org/10.1016/j.jeem.2023.102395

Lera-López, F., Sánchez, M., Faulin, J., & Cacciolatti, L. (2014). Rural environment stakeholders and policy making: Willingness to pay to reduce road transportation pollution impact in the Western Pyrenees. *Transportation Research Part D: Transport and Environment*, *32*. https://doi.org/10.1016/j.trd.2014.07.003

Li, D., Rishi, M., & Bae, J. H. (2023). Regional differences in willingness to pay for mitigation of air pollution from coal-fired power plants in South Korea. *Sustainability*, *15*(24), 16713.

Li, F., Ahmad, R., Abbas, M., & Irfan, M. (2024). Public awareness and willingness to pay for eliminating atmosphere pollution in Pakistan: A case study. *Environment, Development and Sustainability*, *26*(4), 9895–9922. https://doi.org/10.1007/s10668-023-03125-z

Li, Z., & Hu, B. (2018). Perceived health risk, environmental knowledge, and contingent valuation for improving air quality: New evidence from the Jinchuan mining area in China. *Economics and Human Biology*, *31*. https://doi.org/10.1016/j.ehb.2018.07.007

Liu, R., Liu, X., Pan, B., Zhu, H., Yuan, Z., & Lu, Y. (2018). Willingness to pay for improved air quality and influencing factors among manufacturing workers in Nanchang, China. *Sustainability (Switzerland)*, *10*(5). https://doi.org/10.3390/su10051613

Liu, X., Wu, Y., Hu, Y., Liu, D., Zhang, J., Chen, C., Yuan, Z., & Lu, Y. (2016). Government employees' perception of urban air pollution and willingness to pay for improved quality: A cross-sectional survey study in Nanchang, China. *Environmental Science and Pollution Research*, *23*(21), 22183–22189. https://doi.org/10.1007/s11356-016-7204-1

Luechinger, S. (2007). Valuing air quality using the life satisfaction approach. *41*(0), 0–51.

Luechinger, S. (2009). Valuing air quality using the life satisfaction approach. *The Economic Journal*, *119*(536), 482–515. https://doi.org/10.1111/j.1468-0297.2008.02241.x

Maloma, I., & Sekatane, M. B. (2014). Factors that determine the stated willingness to pay for air pollution: A case of Bophelong township. *International Journal of Social Sciences And Humanity Studies*, *6*(2).

Mariel, P., Khan, M. A., & Meyerhoff, J. (2022). Valuing individuals' preferences for air quality improvement: Evidence from a discrete choice experiment in South Delhi. *Economic Analysis and Policy*, *74*, 432–447. https://doi.org/https://doi.org/10.1016/j.eap.2022.03.006

Mitchell, R. C., & Carson, R. T. (2013). *Using surveys to value public goods: The contingent valuation method*. Routledge. https://doi.org/10.4324/9781315060569

Moran, J., NaSuwan, C., & Poocharoen, O. O. (2019). The haze problem in Northern Thailand and policies to combat it: A review. In *Environmental Science and Policy*, *97*. https://doi.org/10.1016/j.envsci.2019.03.016

Mostafanezhad, M. (2021). The materiality of air pollution: Urban political ecologies of tourism in Thailand. *Tourism Geographies*, *23*(4). https://doi.org/10.1080/14616688.2020.1801826

Nezis, I., Biskos, G., Eleftheriadis, K., Fetfatzis, P., Popovicheva, O., Sitnikov, N., & Kalantzi, O. I. (2022). Linking indoor particulate matter and black carbon with sick building syndrome symptoms in a public office building. *Atmospheric Pollution Research*, *13*(1). https://doi.org/10.1016/j.apr.2021.101292

Ortiz, R. A., Markandya, A., & Hunt, A. (2009). Willingness to pay for reduction in immediate risk of mortality related to air pollution in Sao Paulo, Brazil. *Revista Brasileira de Economica*, *63*(1), 3–22. DOI:10.1590/S0034-71402009000100001

Padmanabha, U. R. S., Rajesh, L., Nagarajaiah, P., & Rajappa, M. (2021). Indoor air pollution and its effects on health of women in rural population of Karnataka - A community based survey. *Journal of Evolution of Medical and Dental Sciences*, *10*(33). https://doi.org/10.14260/jemds/2021/550

Papke, L. E. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics*, *11*(6). https://doi.org/10.1002/(SICI)1099-1255(199611)11:6<619::AID-JAE418>3.0.CO;2-1

Pasukphun, N., Rai, C., Mai, C., Son, H., & Nan, T. (2018). Environmental health burden of burning in Northen Thailand: A review. *PSRU Journal of Science and Technology*, *3*(3).

Phairuang, W., Hata, M., & Furuuchi, M. (2017). Influence of agricultural activities, forest fires and agro-industries on air quality in Thailand. *Journal of Environmental Sciences*, *52*, 85–97. https://doi.org/10.1016/j.jes.2016.02.007

Phosri, A., Ueda, K., Phung, V. L. H., Tawatsupa, B., Honda, A., & Takano, H. (2019). Effects of ambient air pollution on daily hospital admissions for respiratory and cardiovascular diseases in Bangkok, Thailand. *The Science of the Total Environment*, *651*(Pt 1), 1144–1153. https://doi.org/10.1016/j.scitotenv.2018.09.183

Pu, S., Shao, Z., Yang, L., Liu, R., Bi, J., & Ma, Z. (2019). How much will the Chinese public pay for air pollution mitigation? A nationwide empirical study based on a willingness-to-pay scenario and air purifier costs. *Journal of Cleaner Production*, *218*. https://doi.org/10.1016/j.jclepro.2019.01.270

Quintyne, K. I., & Kelly, C. (2023). Knowledge, attitudes, and perception of air pollution in Ireland. *Public Health in Practice*, *6*, 100406. https://doi.org/https://doi.org/10.1016/j.puhip.2023.100406

Randall, A., Mitchell, R. C., & Carson, R. T. (1990). Using surveys to value public goods: The contingent valuation method. *Land Economics*, *66*(1). https://doi.org/10.2307/3146688

Saenz-de-Miera, O., & Rosselló, J. (2014). Modeling tourism impacts on air pollution: The case study of PM10 in Mallorca. *Tourism Management*, *40*. https://doi.org/10.1016/j.tourman.2013.06.012

Sánchez-garcía, M., Zouaghi, F., Lera-lópez, F., & Faulin, J. (2021). An extended behavior model for explaining the willingness to pay to reduce the air pollution in road transportation. *Journal of Cleaner Production*, *314*, 128134. DOI: 10.1016/J.JCLEPRO.2021.128134

Seenprachawong, U. (2003). Economic valuation of coral reefs at Phi Phi Islands, Thailand. *International Journal of Global Environmental Issues*, *3*(1). https://doi.org/10.1504/IJGENVI.2003.002413

Shao, S., Tian, Z., & Fan, M. (2018). Do the rich have stronger willingness to pay for environmental protection? New evidence from a survey in China. *World Development*, *105*, 83–94. https://doi.org/https://doi.org/10.1016/j.worlddev.2017.12.033

Srisawasdi, W., Tsusaka, T. W., Winijkul, E., & Sasaki, N. (2021). Valuation of local demand for improved air quality : The case of the Mae Moh coal mine site in Thailand. *Atmosphere*, *12*(9), 1132. https://doi.org/10.3390/atmos12091132

Sterner, T., & Coria, J. (2013). *Policy instruments for environmental and natural resource management* (2nd ed). New York: Routledge.

Sun, C., Yuan, X., & Yao, X. (2016). Social acceptance towards the air pollution in China: Evidence from public's willingness to pay for smog mitigation. *Energy Policy*, *92*, 313–324. https://doi.org/https://doi.org/10.1016/j.enpol.2016.02.025

Syuhada, G., Akbar, A., Hardiawan, D., Pun, V., Darmawan, A., Heryati, S. H. A., Siregar, A. Y. M., Kusuma, R. R., Driejana, R., Ingole, V., Kass, D., & Mehta, S. (2023). Impacts of air pollution on health and cost of illness in Jakarta, Indonesia. *International Journal of Environmental Research and Public Health*, *20*(4). https://doi.org/10.3390/ijerph20042916

Tang, C., & Zhang, Y. (2016). Using discrete choice experiments to value preferences for air quality improvement: The case of curbing haze in urban China. *Journal of Environmental Planning and Management*, *59*(8), 1473–1494. https://doi.org/10.1080/09640568.2015.1079518

Tantiwat, W., Gan, C., & Yang, W. (2021). The estimation of the willingness to pay for air-quality improvement in Thailand. *Sustainability (Switzerland)*, *13*(21). https://doi.org/10.3390/su132112313

Thanh, B. D., & Lefevre, T. (2000). Assessing health impacts of air pollution from electricity generation: The case of Thailand. *Environmental Impact Assessment Review*, *20*(2), 137–158. https://doi.org/https://doi.org/10.1016/S0195-9255(99)00041-4

Thanh, B. D., & Lefevre, T. (2001). Assessing health benefits of controlling air pollution from power generation: The case of a lignite-fired power plant in Thailand. *Environmental Management*, *27*(2), 303–317. https://doi.org/10.1007/s002670010151

Uma, K. E., Nwaka, I. D., Nwogu, M. U., & Obidike, P. C. (2020). What are the triggers of household decision-making on waste disposal choices ? A gender differentiated analysis. *Heliyon*, *6*(12), e05588. https://doi.org/10.1016/j.heliyon.2020.e05588

Vassanadumrongdee, S., & Matsuoka, S. (2005). Risk perceptions and value of a statistical life for air pollution and traffic accidents: Evidence from Bangkok, Thailand. *Journal of Risk and Uncertainty*, *30*, 261–287.

Vassanadumrongdee, S., Matsuoka, S., & Shirakawa, H. (2004). Meta-analysis of contingent valuation studies on air pollution-related morbidity risks. *Environmental Economics and Policy Studies*, *6*(1). https://doi.org/10.1007/BF03353929

Vichit-Vadakan, N., & Vajanapoom, N. (2011). Health impact from air pollution in Thailand: Current and future challenges. *Environmental Health Perspectives*, *119*. https://doi.org/10.1289/ehp.1103728

Wang, B., Hong, G., Qin, T., Fan, W.-R., & Yuan, X.-C. (2019). Factors governing the willingness to pay for air pollution treatment: A case study in the Beijing-Tianjin-Hebei region. *Journal of Cleaner Production*, *235*, 1304–1314. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.07.046

Wang, H., & Mullahy, J. (2006). Willingness to pay for reducing fatal risk by improving air quality: A contingent valuation study in Chongqing, China. *Science of the Total Environment*, *367*(1). https://doi.org/10.1016/j.scitotenv.2006.02.049

Wang, H., & Zhang, X. (2022). Urban residents' willingness to pay for air pollution control in China: A case study of Beijing. *Environmental Science & Policy*, *127*, 1–10. https://doi.org/10.1016/j.envsci.2021.09.014

Wang, K., Wu, J., Wang, R., Yang, Y., Chen, R., Maddock, J. E., & Lu, Y. (2015a). Analysis of residents' willingness to pay to reduce air pollution to improve children's health in community and hospital settings in Shanghai, China. *Science of the Total Environment*, *533*. https://doi.org/10.1016/j.scitotenv.2015.06.140

Wang, K., Wu, J., Wang, R., Yang, Y., Chen, R., Maddock, J. E., & Lu, Y. (2015b). Analysis of residents' willingness to pay to reduce air pollution to improve children's health in community and hospital settings in Shanghai, China. *Science of The Total Environment*, *533*, 283–289. https://doi.org/https://doi.org/10.1016/j.scitotenv.2015.06.140

Wang, Y., Sun, M., Yang, X., & Yuan, X. (2016). Public awareness and willingness to pay for tackling smog pollution in China: A case study. *Journal of Cleaner Production*, *112*, 1627–1634. https://doi.org/https://doi.org/10.1016/j.jclepro.2015.04.135

Wang, Y., & Zhang, Y. S. (2009). Air quality assessment by contingent valuation in Ji'nan, China. *Journal of Environmental Management*, *90*(2). https://doi.org/10.1016/j.jenvman.2008.03.011

Wei, W., & Wu, Y. (2017). Willingness to pay to control PM2.5 pollution in Jing-Jin-Ji Region, China. *Applied Economics Letters*, *24*(11), 753–761. https://doi.org/10.1080/13504851.2016.1226482

Yang, X., Cheng, L., Yin, C., Lebailly, P., & Azadi, H. (2018). Urban residents' willingness to pay for corn straw burning ban in Henan, China: Application of payment card. *Journal of Cleaner Production*, *193*, 471–478. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.05.066

Yoo, S.-H., Kwak, S.-J., & Lee, J.-S. (2008). Using a choice experiment to measure the environmental costs of air pollution impacts in Seoul. *Journal of Environmental Management*, *86*(1), 308–318. https://doi.org/https://doi.org/10.1016/j.jenvman.2006.12.008

Yu, X., & Abler, D. (2010). Incorporating zero and missing responses into CVM with open-ended bidding: Willingness to pay for blue skies in Beijing. *Environment and Development Economics*, *15*(5). https://doi.org/10.1017/S1355770X10000197

Zahedi, S., Batista-Foguet, J. M., & van Wunnik, L. (2019). Exploring the public's willingness to reduce air pollution and greenhouse gas emissions from private road transport in Catalonia. *Science of The Total Environment*, *646*, 850–861. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.07.361

Zhang, B., Zeng, R., & Li, X. (2019). Environmental and human health impact assessment of major interior wall decorative materials. *Frontiers of Engineering Management*, *6*(3), 406–415. https://doi.org/10.1007/s42524-019-0025-4

Zhao, X., Cai, Q., Li, S., & Ma, C. (2018). Public preferences for biomass electricity in China. *Renewable and Sustainable Energy Reviews*, *95*, 242–253. https://doi.org/https://doi.org/10.1016/j.rser.2018.07.017