Prepublished copy

Nature Environment & Pollution Technology

This is a peer-reviewed prepublished version of the paper to be published in Vol. 25, No. 4, December 2026 issue

Original Research

The Value of a Statistical Life of Urban Air Pollution in Ho Chi Minh City, Vietnam

Thu Thi Minh Nguyen[1], Quang Minh Ho Ky[1] and Doan Quang Tri[2]†

[1]Faculty of Engineering and Technology, Sai Gon University

[2]Center for Multidisciplinary Monitoring, Institute of Earth Sciences, Vietnam Academy of Science and Technology, Ha-noi, Vietnam

†Corresponding author: Doan Quang Tri; doanquangtrikttv@gmail.com

ORCID IDs of Thu Thi Minh Nguyen: https://orcid.org/0000-0002-1994-7822

ORCID ID of Doan Quang Tri: https://orcid.org/0000-0003-2376-3222

Key Words	Value of Statistical Life, Willingness to Pay, Air pollution, Binary logistic model, Contingent valuation survey, URBAN environmental quality, Pollution mitigation policies
DOI	https://doi.org/10.46488/NEPT.2026.v25i04.D1930 (DOI will be active only after the final publication of the paper)
Citation for the Paper	Nguyen, T.T.M., Ho Ky, Q.M. and Tri, D.Q., 2026. The value of a statistical life of urban air pollution in Ho Chi Minh City, Vietnam, *Nature Environment and Pollution Technology*, 25(4), D1930. https://doi.org/10.46488/NEPT.2026.v25i04.D1930

ABSTRACT

Although the trade-off between income and environmental quality has received increasing attention in recent years, particularly in Vietnam, empirical evidence on the Value of a Statistical Life (VSL) associated with environmental pollution remains limited. This study addresses this gap by estimating the VSL based on residents' perceptions of air pollution in Ho Chi Minh City, one of Vietnam's largest and most densely populated metropolitan areas. Using data from a contingent valuation survey (N = 879), combined with chi-square analysis and binary logistic regression, we estimate the VSL and examine the factors influencing willingness to pay (WTP) for environmental improvement. The results indicate a VSL of approximately USD 12.4 million, substantially higher than estimates derived from conventional GDP-scaling approaches. Socioeconomic characteristics, including income, age, education, and residential location, were significantly associated with WTP decisions, although the strength of these associations was relatively weak. In addition, the logistic regression analysis identified income and self-reported pneumonia-related symptoms as significant predictors of respondents' willingness to accept income reductions in exchange for improved environmental quality. The model demonstrated satisfactory predictive performance, achieving an AUC above 0.81, classification accuracy exceeding 74%, specificity above 79%, and sensitivity above 68%. These findings contribute to the emerging literature on VSL estimation in developing-country contexts and provide empirical evidence that may support the design and evaluation of urban air-pollution mitigation policies.

1. INTRODUCTION

Air pollution in developing countries, particular populated cities are recently becoming serious. In Ho Chi Minh City, Vietnam, the average concentration of $PM_{2.5}$ from 2013 to 2017 was five times higher than the World Health Organization (WHO) standard, while PM_{10} levels were also approximately five times above the national standard for ambient air quality (EPAVN, 2023; IQAir, 2024; Vu et al., 2021; WHO, 2021). Additionally, air pollution accounts for around 13% of deaths in Ho Chi Minh City, with the majority of these fatalities happening in the city center (Loan, 2018).

Environmental quality, particularly ambient air quality, is a non-market good whose economic value is commonly assessed using individuals' willingness to pay (WTP) for environmental improvements (Baker and Ruting, 2014; Sajise et al., 2021). Previous studies have reported substantial variation in WTP across countries and socioeconomic contexts. In Pakistan, respondents were willing to pay an average of USD 9.86 per month (approximately 1.3% of household income) for improved air quality, with more than 90% expressing a willingness to contribute (Akhtar et al., 2017). Similarly, a survey of 3,000 urban residents in China estimated an average WTP of approximately USD 10 per person per year (Guo et al., 2020). In Vietnam, WTP estimates for air-quality improvement have generally been lower. Residents of Ho Chi Minh City were found to be willing to pay between USD 0.73 and 1.08 per person per month, while households in Hanoi reported an average WTP of USD 3.58 per month (Le and Bui, 2020). Another study in Hanoi estimated that households were willing to allocate up to 0.5% of their total income to improve air quality (Nguyen and Le, 2019). Previous research has identified several determinants of WTP for environmental improvement, including education, occupation, residential location, and perceived environmental conditions (Junlin et al., 2024; Xiong et al., 2018). In the Vietnamese context, income, educational attainment, literacy, and financial capacity have consistently been reported as the primary factors influencing individuals' willingness to pay for better environmental quality (Le and Bui, 2020).

Given the potentially severe health and mortality impacts of environmental degradation, the Value of a Statistical Life (VSL) has become a widely used framework for quantifying mortality risks by examining the trade-offs individuals make between income and reductions in the probability of death (Andersson and Treich, 2013; Colmer, 2020). Although VSL has been extensively investigated in developed countries, empirical studies linking VSL directly to pollution-related risks remain relatively limited in developing economies, including Vietnam. One of the few studies in the region estimated the VSL associated with mortality risks from water-pollution-related diarrheal diseases in Laos and Vietnam (Eiji et al., 2012). More recently, a study evaluating the health benefits of public transportation in Hanoi in the context of fine particulate matter ($PM_{2.5}$) pollution estimated a VSL of approximately USD 1.6 million per person by transferring VSL values from Taiwan and adjusting them using income-based conversion factors (Trung and Tri, 2022).

Although several studies have estimated willingness to pay (WTP) and the value of a statistical life (VSL) in major Vietnamese cities such as Hanoi and Ho Chi Minh City (Le and Bui, 2020; Nguyen and Le, 2019), limited attention has been given to integrating non-parametric and parametric approaches within a unified valuation framework. This study addresses this gap by combining the Turnbull non-parametric estimator with binary logistic regression. To the best of our knowledge, the application of this integrated framework to air-pollution-related VSL estimation remains largely unexplored in developing-country contexts, including Vietnam. The Turnbull estimator provides a conservative, distribution-free estimate derived directly from the observed bid-response data (Haab and Connell, 2002), thereby reducing reliance on restrictive distributional assumptions. Complementarily, the binary logistic model enables the identification of socioeconomic and health-related determinants underlying respondents' willingness to pay. By integrating these two approaches, the study not only generates a robust VSL estimate for Ho Chi Minh City but also provides insights into the factors shaping individual risk-reduction preferences in an urban environment affected by air pollution.

Therefore, this study aims to calculate the actual VSL value of air pollution in Ho Chi Minh City, Vietnam, by applying the WTP tool, which is the monetary value a person would trade to reduce their annual mortality rate by one unit. The results of this study can support accurately determining the social VSL value in large urban areas in Vietnam, and provide the basis for decision makers to determine the amount of money needed to devote in protection and improvement projects for surrounding air quality.

2. MATERIALS AND METHODOLOGY

2.1. Materials

2.1.1. Study area

Ho Chi Minh City (HCMC) is located in southern Vietnam between 10°10'–10°38' N and 106°22'–106°54' E. As the country's largest economic center, the city serves as a major transportation hub linking surrounding provinces, an international gateway, and a strategic transition zone between the Southeast Region and the Mekong Delta.

Ambient air quality in HCMC is monitored through a network of environmental monitoring stations distributed across the city. Recent assessments indicate that air pollution is primarily driven by particulate matter and noise pollution. Concentrations of Total Suspended Particulates (TSP) and PM_{10} have shown increasing trends, particularly in densely populated areas, industrial zones, seaports, and mining sites. More importantly, $PM_{2.5}$ concentrations at several traffic and industrial monitoring stations exceeded national standards by 1.1–4.6 times (Phan, 2025).

Industrial activities constitute an important source of air pollution in HCMC. Major emission sources include clinker and cement production facilities, chemical and fertilizer plants, petrochemical processing facilities, and industries operating large-scale boilers. In terms of emission loads, the textile and food-processing sectors are among the largest contributors. The textile industry alone accounts for approximately 37% of TSP emissions and 41% of $PM_{2.5}$ emissions, largely due to intensive fuel consumption (e.g., LPG, fuel oil, diesel oil, firewood, and biomass briquettes) and the release of fabric and fiber dust. In addition, textile dyeing and finishing processes generate substantial emissions of non-methane volatile organic compounds (NMVOCs) through activities such as sizing, scouring, bleaching, dyeing, and finishing (DONRE, 2021).

Transportation represents the dominant source of air pollution in the city. According to DONRE (2021), the transport sector contributes approximately 99%, 97%, 93%, 78%, 23%, 64%, and 45% of total emissions of CO, NMVOCs, NO_x, SO_2, TSP, CH_4, and $PM_{2.5}$, respectively. Road transport, particularly motorcycles, accounts for nearly 90% of transport-related emissions and is responsible for approximately 75% of transport-generated $PM_{2.5}$ emissions. River and seaport activities contribute around 24% of $PM_{2.5}$ emissions, whereas aviation contributes only about 1%, and emissions from railway and bus terminal operations remain negligible (DONRE, 2021).

2.1.2. Sample size

The study applied a random sampling method, with the assumption that there is a proportion of the population willing to lessen the income to reduce mortality rate from air pollution, the sample size was therefore calculated according to formula (1) (Daniel and Cross, 2013; Singh and Masuku, 2013).

$$n = \frac{z^2 * p\,(1 - p)}{\varepsilon^2} \tag{1}$$

where z is the corresponding z-score value; ε is the margin of error; p is the proportion of the selected population. With a proportion of the selected population of 50% to archive the highest minimum sample size, the minimum sample size required is 385.

From April 2024 to March 2025, participants were recruited using an online convenience sampling approach through digital platforms and community networks in Ho Chi Minh City. Of the 1,007 questionnaires collected, 879 valid responses were retained for analysis. The sample was predominantly urban, with 85% of respondents residing in central urban districts. The average monthly income was approximately VND 10 million (USD 380), and 70% of respondents reported monthly incomes below VND 20 million (USD 760), broadly consistent with official statistics for Ho Chi Minh City (Vietnam General Statistics Office, 2025). More than 50% of respondents held a university degree or higher, exceeding the citywide average of 15–27% reported in previous studies and official sources (Le, 2018; Thanh, 2025). This difference likely reflects the online recruitment strategy, which tends to attract individuals with higher educational attainment and greater engagement with environmental issues. While this may limit the representativeness of the sample, it is consistent with the increasing adoption of digital platforms and the city's ongoing digital transformation initiatives (Thanh, 2025).

2.2. Methods

The methodology and research design are illustrated in Figure 1 as follows:

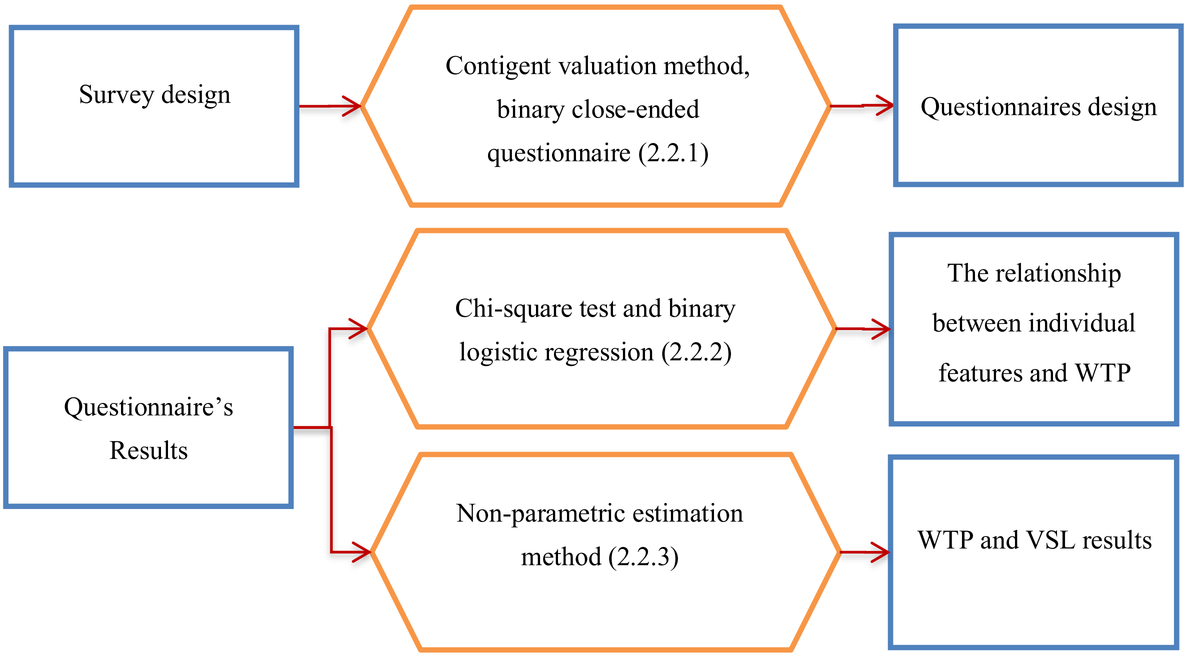


Fig 1: Methodological framework

2.2.1. The Contingent Valuation methods

The Contingent Valuation (CV) method employs a structured survey to elicit respondents' willingness to pay (WTP) for a specified environmental improvement. First introduced by Ciriacy-Wantrup (1947), the method has been widely applied in environmental valuation, including studies of environmental quality, ecosystem services, and waste management, and has demonstrated satisfactory reliability in estimating non-market values (Bodah et al., 2022; Hoevenagel, 1994; Perni et al., 2021; Tang et al., 2022; Thormann and Wicker, 2021). In dichotomous-choice CV surveys, respondents are presented with a bid amount and asked whether they would be willing to pay that amount. Consequently, individual WTP is represented as an interval bounded by the respondent's acceptance or rejection of successive bid levels.

To reduce the potential for hypothetical bias and WTP overestimation, particularly in the valuation of public goods (Andersson and Treich, 2013; Vincent Biausque, 2012), the questionnaire incorporated measures of response certainty and consistency (Hoyos and Mariel, 2010; Sajise et al., 2021; Sundström and Andersson, 2009). The survey consisted of 35 questions (H1–H35) organized into five sections. The first section included four questions designed to assess respondents' perceptions of air-pollution risks and their understanding of pollution sources. The second section comprised 14 questions addressing self-reported health conditions and symptoms potentially associated with urban air pollution. The third section contained three questions examining respondents' preferences regarding trade-offs between income and health; responses in this section were also used to identify potentially inconsistent answers. The fourth section included eight closed-ended valuation questions related to a hypothetical air-pollution mitigation program. Under this scenario, the program was assumed to reduce the mortality risk from 48 to 47 deaths per 10,000 individuals, equivalent to a reduction of one death per 10,000 population (Nhung et al., 2022). The final section collected socio-demographic information from respondents.

In the study, participants will be presented with five bid ranges that are developed based on the average income in Ho Chi Minh City of approximately 379 USD per month (Vietnam General Statistics Office, 2025) by applying the exchange rate of approximately 26,390 VND/USD. To ensure the structural validity of the method, the survey underwent a calibration procedure. Prior to the official launch, the survey instrument was refined through a focused pilot pre-test and detailed consultations with environmental economists. To mitigate potential starting-point bias (anchoring effects), starting-point bid levels were randomly distributed across different questionnaire versions to ensure independent valuations. Furthermore, the bid range was bounded between a minimum of 11,000 VND (~0.48 USD, referencing a standard 500ml bottled water in a convenience store) and a maximum cap of 500,000 VND (~21.74 USD). This upper boundary represents approximately 5% of the average local monthly income; pilot feedback indicated that exceeding this threshold would trigger widespread protest responses and scenario rejections.

Figure 2 outlines the relationship between the bids and WTP estimates. In the figure, it is suggested that the bids are correspondent to 0.35%, 1%, 3% and 5% of the monthly income, equivalent to 0.43, 1.52, 4.35, 13.04, and 21.74 USD. At the extremities of these ranges, open-ended questions will be administered to enable respondents to specify their own maximum WTP. The questions regarding current health status and perceptions of air pollution use a 5-point Likert scale for responses.

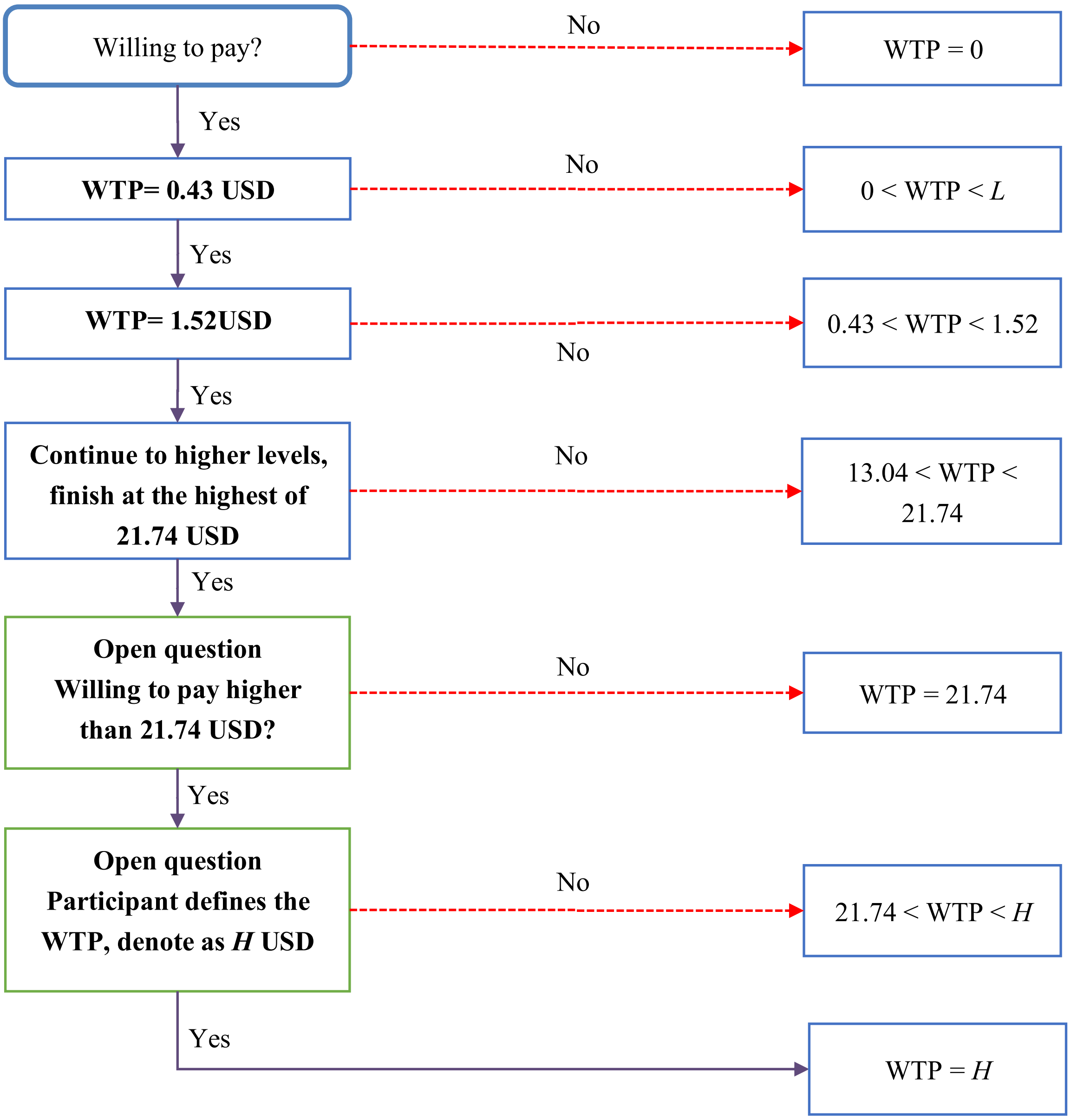


Fig. 2: Contingent valuation survey design.

2.2.2. Factors evaluation

- Chi square test

Chi-square test is a statistical hypothesis testing method to determine the relationship among categorical variables. The method has been widely applied in recent studies to investigate the connection between the socio-demographic factors and the respondent's decision (Ali and Ali, 2020; Dhungana and Baral, 2016; Karytsas et al., 2019). In the study, the test method was applied to test the relationship between the decision to reduce income and personal characteristics, including age, gender, income, education level, and residency. The test model is based on the chi-square formula as follows:

$$\lambda^2 = \sum \frac{(O - E)^2}{E} \tag{2}$$

where O is the observed value, and E is the estimated value.

- Binary Logistic Regression

This is a statistical method that uses one or more independent variables to predict the probability of a binary outcome for a dependent variable. The method has been applied in studies including research on environmental resources valuation (Hu et al., 2022; Yulianus and Riaman, 2021). In the study, as the 25th question (H_{25}) is the dependent variable, the formula is therefore as follows:

$$P(H_{25} = 1) = \frac{e^{(\beta_0 + \sum_{i=1}^{24} \beta_i H_i)}}{1 + e^{(\beta_0 + \sum_{i=1}^{24} \beta_i H_i)}} \tag{3}$$

where $P(H_{25} = 1)$ is the probability that the variable H_{25} takes the value of 1, in which H_{25} takes one of two values: 0 (disagree) and 1 (agree), and β_i is the corresponding parameter of the independent variable H_i, which i ranges from 1 to 24.

The logistic regression model needs to be assessed for accuracy, reliability, and sensitivity according to the parameters in Table 1 (Criado and Veronesi, 2013).

Table 1: Model evaluation parameters

		Modelled observation		**Total**
		0	**1**	
Actual observation	**0**	TN	FP	ON = TN + FP
	1	FN	TP	OP = FN + TP

(Note: T = True, F = False, N = Negative, P = Positive, O = Observed)

TN and TP are “True Negative” and “True Positive”. They arise when the predicted value is identical to the actual observation. FN and FN are “False Negative” and “False Positive”, happened when the predicted and actual values are different. ON is Observed Negative, and OP is Observed Positive.

The evaluation parameters are calculated as follows:

Accuracy: CCR = (TN+TP)/n (3)

Sensitivity: TPR = TP/OP (4)

Significance: SPC = TN/ON (5)

2.2.3. Non-parametric estimation methods

- WTP estimation based on Turnbull lower bound non-parametric estimation

Non-parametric estimation is widely applied in recent researches to estimate WTP values for non-market goods (Giolo, 2004; Hutchinson et al., 2001; Loureiro et al., 2004; Ranneby and Yu, 2011). The method is described with a sample of T individuals who are offered one of B monetary amounts, denoted B_j (where $B_1 < B_2 < \ldots < B_n$). The willingness to pay (WTP_i) for each individual i is modeled as a random variable according to F distribution (Angelov and Ekström, 2017; Giolo, 2004; Haab and Connell, 2002), as follows:

$$P(WTP_j < B_j) = F(B_j) = F_j \tag{6}$$

F_j is considered the cumulative acceptance rate for the bid B_j, and is estimated as follow:

1. Assemble bids from the smallest to largest B_j, where j = 1, …, M

2. Calculate F_j and T_j:

$$F_j = N_j/T_j \text{ and } T_j = N_j + Y_j \quad (7)$$

Where: N_j is the number of individuals taking "No" and Yj is the number of individuals selecting "Yes" at the bid B_j; $F_j = P(WTP \le 0)$. F_j is then adjusted to F^*_j as follow:

3. Compare F_j with $F_{(j+1)}$:

If $F_j \le F_{(j+1)}$, then set $F^*_j = F_j$ and continue with $j = j + 1$;

If $F_j > F_{(j+1)}$, then proceed to merge the two bids steps B_j and $B_{(j+1)}$ into one group with the upper and lower bounds being $[B_j, B_{(j+2)}]$ and computing F^*_j:

$$F^*_j = (N_j + N_{(j+1)})/(T_j + T_{(j+1)}) \quad (8)$$

4. Repeat the step until a monotonically increasing series is built. The probability density of willingness to pay f^*_j from the bid B_j and $B_{(j+1)}$ is then calculated as follow:

$$f^*_j = F^*_{(j+1)} - F^*_j \quad (9)$$

5. Set the last cumulative probability $F^*_{(M+1)}$ is 1, the mean WTP is estimated as follow:

$$WTP = \sum B_j f^*_{(j+1)} \quad (10)$$

- VSL estimation

VSL is an economic metric used in cost-benefit analysis to estimate the monetary value an individual place on reducing the risk of premature death. It reflects the aggregate WTP across a population for small mortality risk reductions. Consequently, studies often show a strong correlation between VSL and income (Cropper et al., 2011; Viscusi and Aldy, 2003), and lower VSL is also placed on public goods than on private goods (Vincent Biausque, 2012). It, therefore, is obtained by taking the limit of WTP or WTA (Willingness to Accept) when the change in risk is infinitesimal, calculated in formula 11.

$$VSL = \frac{w}{p(1-\gamma)} \text{ and } \gamma \in [0,1] \quad (11)$$

Where w is individual's wealth, p is the individual' survival rate in a period of time. In other words, VSL is the positive slope between the change in wealth and the probability of death, illustrated in Figure 3 (Andersson and Treich, 2013; Hammitt, 2000).

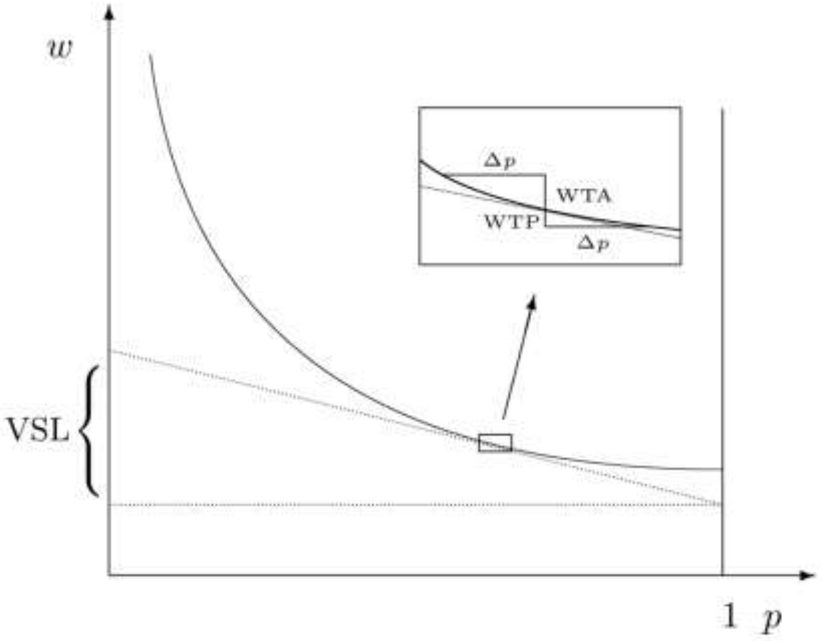


Fig. 3: Theoretical VSL value according to wealth (w) and survival probability (p).

In practice, VSL is estimated based on the WTP as shown in equation 12 (Criado and Veronesi, 2013; Kenkel, 2003; Kniesner and Viscusi, 2019).

$$\mathrm{VSL} = \frac{\mathrm{WTP}}{\mathrm{d_r}} \tag{12}$$

where VSL: the statistical value of life corresponding to the risk reduction d_r; WTP: the individual's willingness to pay, obtained by closed-ended question contingent valuation method; d_r: the achieved risk reduction.

In this study, the risk reduction is defined as a decrease of one unit (from 48/10,000 to 47/10,000). The expressed WTP therefore directly measures the economic value of one VSL. Therefore, under this specific design framework, the estimated WTP value is mathematically equivalent to the VSL.

3. RESULTS

The initial dataset was refined by excluding 128 questionnaires identified as containing either outlier responses or internal inconsistencies. Internal inconsistencies were assessed by cross-checking responses across the survey sections. Questionnaires were flagged when respondents reported low perceived risk or no air-pollution-related health impacts (H_1–H_{18}) but subsequently stated implausibly high willingness-to-pay (WTP) values. In addition, responses were excluded when participants indicated limited financial capacity in the validation questions but selected high payment bids for the proposed mitigation program.

Outliers were identified through a two-stage screening process. First, anomalous WTP responses were flagged using Excel-based filtering procedures. Second, all flagged questionnaires were manually reviewed across the full set of survey questions, including socio-demographic information, to verify and remove invalid observations. Following this quality-control process, 879 valid responses were retained for subsequent analysis.

3.1. Results of the influencing factors

3.1.1. Relationship between demographic information and the decision to reduce income

A chi-square test was applied to examine the relationship between demographic information (H_1 to H_5) and the decision to reduce income (H_{25}). The result revealed that demographic factors, including income (H_1), age (H_2), educational level (H_4), and residence (H_5), were all found to be significantly associated with the respondents' decision (Table 2). Besides, Cramer's V and the Contingency coefficient were also employed to assess the strength among variables. The analysis yielded values between 0.1 and 0.3, signifying a weak relationship among all the variables.

Table 2: Chi-square statistics of H_{25} versus demographic variables

Influencing variables	Chi-square value	p-value	Contingency coefficient	Cramer's V
Income (H_1)	46.8	0.000	0.225	0.231
Education (H_4)	49.0	0.000	0.198	0.202
Age (H_2)	22.2	0.000	0.157	0.159
Residence (H_5)	18.3	0.003	0.143	0.144
Gender (H_3)	2.0	0.161	-	-

- Income and Education

Among all variables analyzed, income and education emerged as the primary determinants, yielding the highest Cramer's V and Contingency coefficients. The categorical divergence within these factors is illustrated in Figure 4.

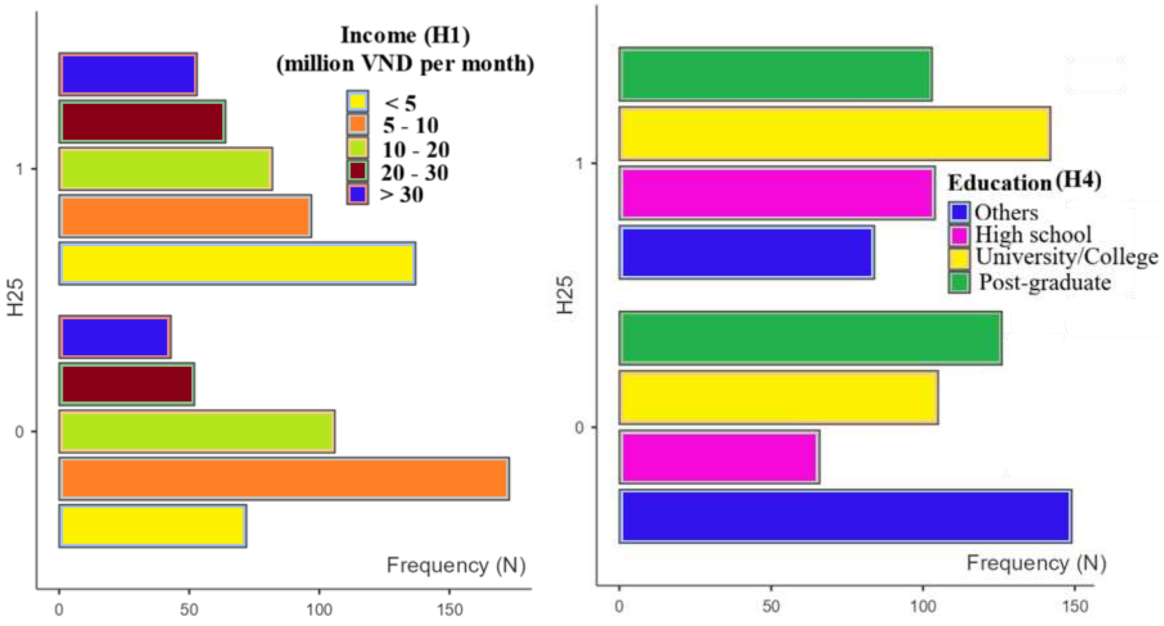


Fig. 4: The relationship among income and education to the respondents' decision.

The lowest income group exhibited the strongest inclination toward "Yes" responses, with the frequency more than doubling that of "No" choices. Conversely, the 5–10 million VND group showed a sharp reversal, where “No” responses peaked at over 64%. While the mid-to-high income segments maintained a stable preference for “No”, a notable shift occurred in the two highest groups (more than 20 million VND per month), the “Yes” rate regained slight dominance, converging at 55.2% for both. Besides, respondents with High School or Undergraduate/College backgrounds leaned toward “Yes” (61% and 58%, respectively). In contrast, those in other categories, particularly those with Postgraduate degrees, demonstrated a higher propensity for “No” responses.

- Age and Residence

Age and Residence exhibited statistically significant but relatively weak associations with the decision-making outcome, with Cramer's V coefficients of 0.159 and 0.144, respectively. These patterns are illustrated in Figure 5.

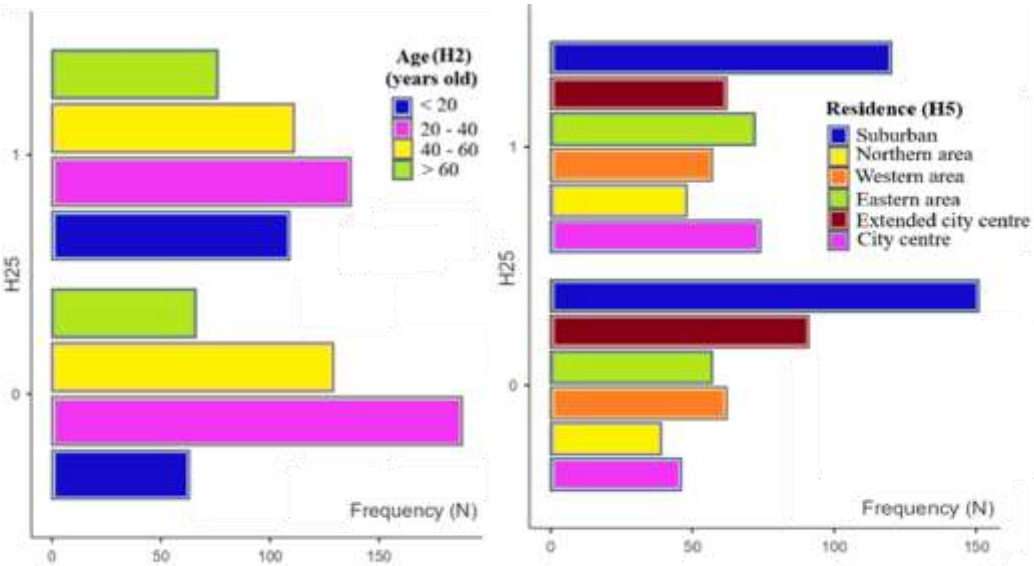


Fig. 5: The relationship among age and residence to the respondents' decision

Age-related differences were observed in respondents’ choices. The highest proportion of “Yes” responses was recorded among respondents under 20 years of age (63%), whereas those aged 20–60 years showed a slight preference for “No” responses (53%–58%). Among respondents aged over 60 years, the share of “Yes” responses increased to 53.5%.

Spatial patterns were similarly modest. Respondents residing in suburban areas and the eastern and northern urban districts were somewhat more likely to select “Yes” (67.0%, 55.8%, and 55.2%, respectively), while respondents from other areas showed a slight preference for “No”. Overall, the observed differences across residential groups were relatively limited.

3.1.2. Possibility to reduce income to improve environmental quality

- The binary logistic model

Binary logistic regression was employed to identify factors influencing respondents’ willingness to accept a reduction in income in exchange for improved environmental quality (H_{25}). Independent variables included demographic characteristics and self-reported health-related indicators. Among the variables examined, the perceived importance of health relative to income (H_{10}) and self-reported pneumonia-related symptoms (H_{15}) were significantly associated with the probability of accepting reduced income for environmental improvement. The results are reported in Table 3.

Table 3: The model' summary

	B	SE	Odds Ratio	Wald Statistic	p -value
(Intercept)	2.936	0.548	18.832	33.652	< .001
H10	0.982	0.079	2.670	138.386	< .001
H15	-1.399	0.122	0.247	128.559	< .001

Both H_{10} and H_{15} were statistically significant predictors of the outcome variable ($p < 0.05$). The relatively small standard errors indicate stable coefficient estimates, while the large Wald statistics demonstrate the substantial contribution of these variables to the model. Compared with the intercept term, H_{10} and H_{15} account for a considerably greater proportion of the model's explanatory power, highlighting their importance in predicting respondents' willingness to accept income reductions for environmental improvement.

The negative coefficient associated with H_{15} indicates an inverse relationship with the probability of a positive response to H_{25}. Specifically, as H_{15} increases by one point on the five-point Likert scale, the odds of a positive response to H_{25} are multiplied by 0.247, corresponding to a reduction of approximately 75.3% in the odds. In contrast, H_{10} (income level) exhibits a positive association with H_{25}. A one-unit increase in H_{10} is associated with a 2.67-fold increase in the odds of a positive response to H_{25}, suggesting that respondents with higher income levels are more likely to provide a positive response.

From these results, the logistic probability function for a respondent's willingness to agree, conditioned on variables H_{10} and H_{15}, is defined in the formula 13 as follows:

$$\mathrm{Ln}\left(\frac{\mathrm{P}}{1-\mathrm{P}}\right) = 2.936 + 0.982 * \mathrm{H}_{10} - 1.399 * \mathrm{H}_{15} \quad (13)$$

To assess the stability and robustness of the logistic regression model, multicollinearity diagnostics were conducted for the independent variables H_{10} and H_{15}. The results are presented in Table 4.

Table 4. Multicollinearity Diagnostics

	Tolerance	VIF	Correlation between H_{10} and H_{15}
H_{10}	0.785	1.274	-0.464
H_{15}	0.785	1.274	

As shown in Table 4, both variables exhibit a Variance Inflation Factor (VIF) of 1.274, well below the commonly accepted threshold of 5.0, while the corresponding Tolerance value of 0.785 exceeds the minimum recommended level of 0.20. In addition, the correlation coefficient between the variables (-0.464) is substantially lower than the critical threshold of 0.70. Collectively, these diagnostics indicate that multicollinearity is not a concern in the present study (Hair et al., 2019).

- The model's performance

The projecting capability is assessed by the parameters shown in Table 5. The model yields an Area Under the Curve (AUC) of 0.814, signifying a high degree of discriminatory power in distinguishing between categorical outcomes. This is complemented by an F-measure of 0.722, which confirms a stable equilibrium between Sensitivity and Precision, ensuring that the model minimizes both Type I and Type II errors.

Table 5: Model's evaluation parameters

AUC	Precision	F-measure	Brier score	H-measure
0.814	0.765	0.722	0.172	0.360

The reliability of predictors H_{10} and H_{15} is further substantiated by an Accuracy of 0.741 and a Precision of 0.765. Particularly, the Specificity of 0.796 exceeds the Sensitivity (0.684), suggesting that the model is significantly adept at identifying "disagreement" cases ($H_{25} = 0$). This characteristic is vital for mitigating the risks associated with false-positive predictions in decision-making. Furthermore, the Brier Score of 0.172, which is approaching the ideal value of zero, indicates that the predicted probabilities are closely aligned with empirical observations. While a numerical disparity exists between the AUC (0.814) and the H-measure (0.360), this is expected given the H-measure's more stringent treatment of cost-weighted misclassifications. Nevertheless, an H-measure of 0.360 (falling within the 0.3–0.5 range) reflects a highly satisfactory level of predictive effectiveness for behavioral modeling.

A robust approach to evaluating the model's classificatory efficiency involves the Receiver Operating Characteristic (ROC) curve, performed in Figure 6. The ROC curve (representing model performance) exhibits a strong trajectory toward the upper-left quadrant. This trend indicates that the model achieves high Sensitivity while maintaining a low False Positive Rate, confirming its robust discriminatory capability.

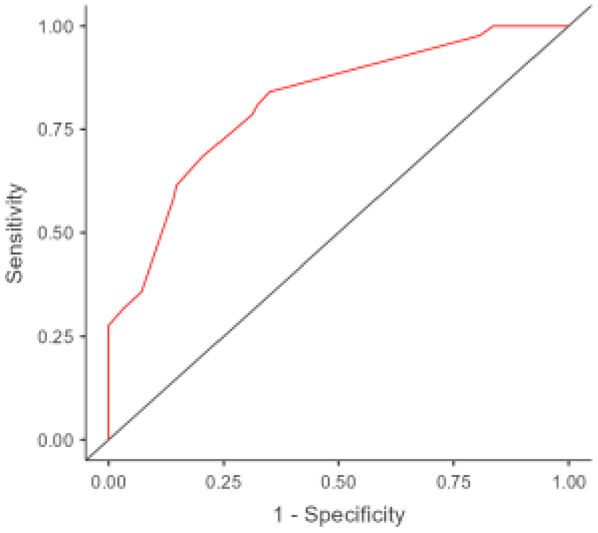


Fig. 6: The Receiver Operating Characteristic (ROC)

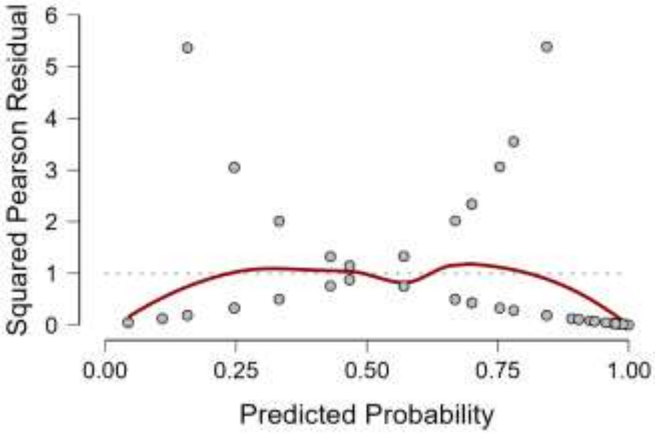


Fig. 7: The Squared Pearson residuals plot

Regarding the assessment of model fit and diagnostic residuals, Figure 7 presents the Squared Pearson Residuals plot, yielding several critical insights. The high concentration of data points near the baseline (zero) demonstrates that the model aligns exceptionally well with the vast majority of the empirical data. The presence of isolated observations with values exceeding 5 identifies specific outliers. These points warrant careful consideration as they may potentially attenuate the overall predictive accuracy of the model. The red trend line, which depicts the mean residual path, shows a low-swept profile with a minimal gradient. This suggests that the error distribution remains relatively stable across all probability bands, reinforcing the model's consistency in behavioral prediction.

The Hosmer–Lemeshow test was significant ($\chi^2 = 25.814$, df = 5, $p < 0.001$), suggesting some deviation between observed and predicted probabilities. However, because this test is highly sensitive to large sample sizes (N = 879) and may overreject well-fitting models (Hosmer et al., 2013; Paul et al., 2013), model fit was evaluated primarily using pseudo-R^2 statistics and predictive validation metrics (Table 6).

Table 6. Model's summary

	Deviance	**AIC**	**BIC**	**df**	**ΔX^2**	**p**	**McFadden R^2**	**Nagelkerke R^2**	**Tjur R^2**	**Cox & Snell R^2**
M_0	1218.4	1220.36	1225.139	878			0.000		0.000	
M_1	894.9	900.94	915.279	876	323.42	< .001	0.265	0.410	0.315	0.308

Note: M_0 is no-variable model; M_1 includes H_{10}, H_{15}

The model showed good explanatory performance, with a Nagelkerke R^2 of 0.410 and a McFadden R^2 of 0.265, values generally considered indicative of a satisfactory fit in discrete choice models (Hosmer et al., 2013; McFadden, 1977). Furthermore, model deviance decreased from 1218.4 for the null model to 894.9 for the fitted model, corresponding to a highly significant likelihood-ratio test ($\Delta\chi^2 = 323.418$, $p < 0.001$). These findings indicate that the proposed model substantially improves upon the null specification and captures a meaningful proportion of the variation in the response variable.

- Model Predictive Performance

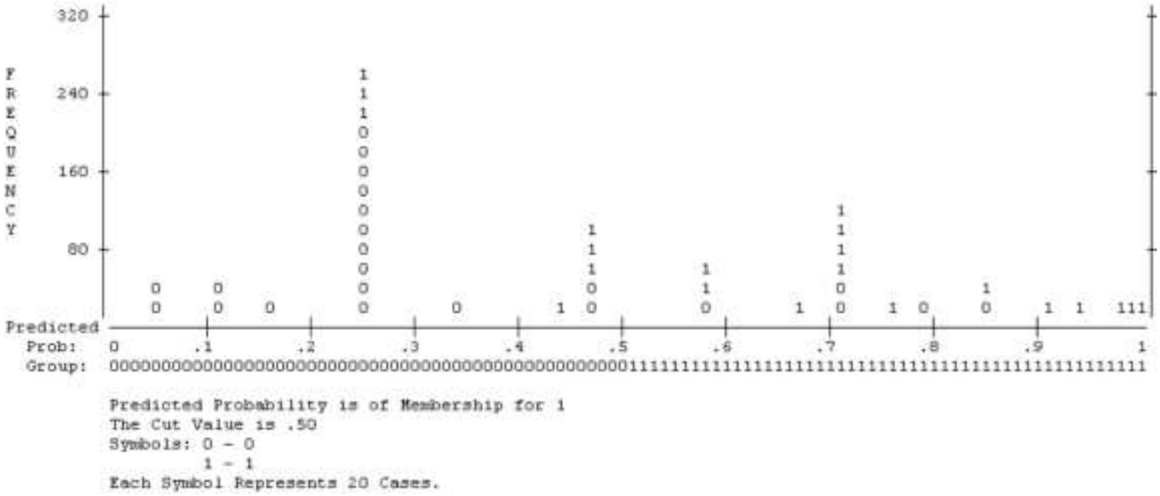
The predictive performance of the binary logistic regression model was assessed using a classification matrix. The corresponding results are reported in Table 7.

Table 7: Classification matrix for the binary logistic model

		Predicted Observation		**% Correct**
		0	**1**	
Actual Observation	**0**	355	91	79.6
	1	137	296	68.4
	Total	492	387	74.1

The model correctly predicted 651 cases out of a total of 879 observations, yielding an Overall Accuracy of 74.1%. For "No" responses (Value 0), the model correctly predicted 355 cases out of 446 actual observations, achieving a Specificity (True Negative Rate) of 79.6%. For "Yes" responses (Value 1), the model correctly predicted 296 cases out of 433 actual observations, achieving a Sensitivity (True Positive Rate) of about 68.4%.

The distributions of the dependent variable H_{25} between actual and predicted values from the model are shown in Figure 8. In the Figure, the frequency distribution can be explained well with the values of 0, evidenced by the alike actual and predicted values which concentrated in the left corner of the graph, and showing a prediction accuracy rate higher than 79%. For the values of 1, the model predicts fairly well, with the majority of observed and predicted values concentrated in the right corner of the graph, and a prediction accuracy rate of over 68%.



```
Predicted Probability is of Membership for 1
The Cut Value is .50
Symbols: 0 - 0
         1 - 1
Each Symbol Represents 20 Cases.
```

Fig. 8: Observed and Predicted Probability Distribution

- Model validation

To evaluate the predictive performance and generalizability of the logistic regression model, the dataset (N = 879) was randomly partitioned into training (70%; n = 616) and testing (30%; n = 263) subsets. The model was developed using the training data and subsequently evaluated on the independent test set. All analyses were conducted in JASP, and the validation results are reported in Table 8.

Table 8. The cross-validation test's results

	0	**1**	**Average/ Total**
Precision (Positive Predictive Value)	0.712	0.812	0.764
Recall (True Positive Rate)	0.825	0.693	0.757
False Positive Rate	0.307	0.175	0.241
False Discovery Rate	0.288	0.188	0.238
F1 Score	0.765	0.748	0.756
Matthews Correlation Coefficient	0.522	0.522	0.522
Area Under Curve (AUC)	0.759	0.759	0.759
Negative Predictive Value	0.812	0.712	0.762
True Negative Rate	0.693	0.825	0.759
False Negative Rate	0.175	0.307	0.241
False Omission Rate	0.188	0.288	0.238

The model exhibited satisfactory predictive performance on the independent test set, with an accuracy of 0.757, an F1 score of 0.756, and an AUC of 0.759. The modest decline in AUC relative to the full-sample estimate (0.814) indicates that the model generalizes well to unseen data and is not substantially affected by overfitting.

The corresponding ROC tracks are illustrated in Figure 9.

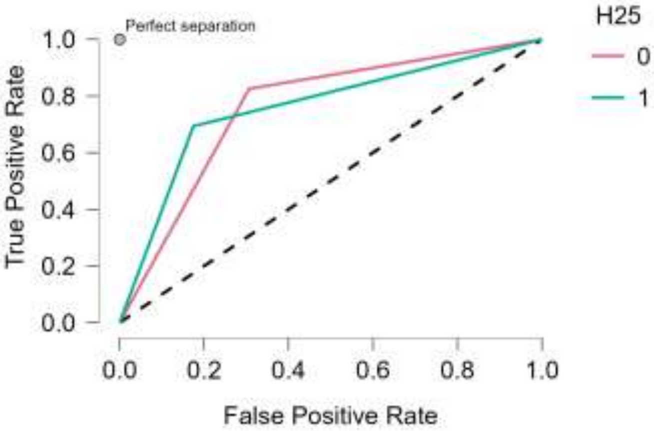


Fig. 9: The Receiver Operating Characteristic (ROC) of the cross-validation test

Figure 9 shows that the ROC curves for both classes remain substantially above the random-classification reference line and trend toward the upper-left corner of the plot. This pattern indicates satisfactory classification performance and provides additional evidence of the model's robustness and generalizability.

3.2. The WTP and VSL's results

The study was designed to estimate the WTP for a one-unit reduction in the risk of death (from 48 to 47 deaths per 10,000 people). In the survey, respondents demonstrated a clear division when comparing personal health and income: 38% prioritized health, 20% prioritized income, and 42% considered them equally vital. However, this willingness to prioritize health did not translate into economic sacrifice. When faced with reducing income for better environmental quality, more than 70% dissented, overwhelmingly citing insufficient income as the primary barrier.

The results of the Turnbull lower bound estimate show that the aggregate WTP that each person is willing to pay is 17.9 thousand VND, presented in Table 9. With the average population of the city being 9.5 million people (Ho Chi Minh City's Department of Health, 2025), the estimated VSL is over 170.2 billion VND, approximately 12.4 million USD. The findings reveal a VSL value 7.8 times higher than the estimates derived from Taiwan's GDP in the 2021 study (Trung and Tri, 2022). While the prior research focused specifically on public transport in Hanoi, the current results underscore a substantial discrepancy between empirical VSL data and theoretical GDP-based estimations.

Table 9: WTP's results according to Turnbull lower bound estimation

B_j (USD)	B_j (1,000 VND)	N_j	F_j	F^*_j	f^*_j	WTP_j (1,000 VND)
0	0	638	0.726	0.726	0.076	0.000
0.43	10	705	0.802	0.802	0.077	0.774
1.52	35	773	0.879	0.879	0.051	1.792
4.35	100	818	0.931	0.931	0.027	2.730
13.04	300	842	0.958	0.958	0.042	12.628
21.74	500	879	1.000	1.000	0.000	0.000
					Total estimated WTP	**17.924**

VSL is frequently estimated using a simplistic approach based on GDP per capita, which is approximately 70 times the value of GDP per capita. This estimation method is widely adopted due to its practical convenience, as it allows for an immediate, preliminary valuation without requiring extensive primary data collection (Woolley et al., 2015; World Bank, 2021). According to the city authorities, the GRDP per capita for the local population in 2024 is approximately USD 7,600 USD. Applying this rule of thumb, the estimated VSL would be USD 532,000, and critically, 22 times lower than the value derived from the Turnbull method.

4. CONCLUSIONS AND DISCUSSION

The research's results indicate an average WTP of more than 17,900 VND per person to achieve a reduction in the air pollution-related mortality rate from 48/10,000 to 47/10,000. Aggregating this value yields an estimated total VSL of 170.2 billion VND, equivalent to 12.4 million USD. A significant finding is the constraint imposed by income, more than 70% (638/879) of the total respondents disagreed to pay, primarily citing insufficient income as the reason. This financial constraint is evidenced by the fact that the group with an income under 20 million VND exhibited the highest refusal rate among all income groups.

Moreover, socio-economic factors, including income, age, education level, and residence, were found to be significantly related to the respondents' WTP decision, though these linkages are relatively week. Economic conditions (income) and education play a more dominant role than biological factors (age) or geographical factors (place of residence) in determining payment decisions. The results of the chi-square model also identified the most likely to agree group as those under 20 years old, high school education, earning less than 5 million VND/month, and residing in suburban/ urban expansion in Northern or Eastern areas.

The probabilistic model for the influencing factors to the income reduction decision (or agree to pay) simultaneously revealed that respondents' assessments of health symptoms played an important role in predicting. The probabilistic model also demonstrated reasonably good predictive values, with an overall correct prediction rate of over 74%, and the efficiency of about 81%.

The results of this study indicate that the residents of Ho Chi Minh City (HCMC) are highly aware of the harmful effects of air pollution on their health. However, when connecting this awareness to their income, less than 30% of the surveyed individuals approved to reduce their income (agreed to pay). The segmentation analysis revealed that the group with medium-high income, who are young, and whose residence is concentrated in the city center, exhibited the highest tendency to agree.

Therefore, further specialized research focusing on the remaining demographic groups is proposed to identify underlying causes. This information can then be used to develop appropriate and effective communication and outreach strategies.

6. PATENTS

Author Contributions: Conceptualization, Thu Thi Minh Nguyen and Quang Minh Ky Ho; methodology, Thu Thi Minh Nguyen; software, Quang Minh Ky Ho; validation, Thu Thi Minh Nguyen, Quang Minh Ky Ho and Doan Quang Tri; formal analysis, Thu Thi Minh Nguyen; investigation, Thu Thi Minh Nguyen; resources, Thu Thi Minh Nguyen; data curation, Thu Thi Minh Nguyen; writing—original draft preparation, Thu Thi Minh Nguyen; writing—review and editing, Thu Thi Minh Nguyen, Quang Minh Ky Ho and Doan Quang Tri; visualization, Thu Thi Minh Nguyen; supervision, Doan Quang Tri; project administration, Thu Thi Minh Nguyen; funding acquisition, Quang Minh Ky Ho. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Sai Gon University, grant number CSB2023-42.

Informed Consent Statement: Not applicable.

Acknowledgments: The authors would like to thank to the support and fund of Sai Gon University, Ho Chi Minh City, Vietnam

Conflicts of Interest: The authors declare no conflicts of interest.

REFERENCES

Akhtar, S., Umer, W., Nadeem, V.M. and Shahid, I. 2017. Assessment of willingness to pay for improved air quality using contingent valuation method. *Global Journal of Environmental Science and Management*, 3, pp.279–286. https://doi.org/10.22034/gjesm.2017.03.03.005.

Ali, T. and Ali, J. 2020. Factors affecting the consumers' willingness to pay for health and wellness food products. *Journal of Agriculture and Food Research*, 2, pp.100076. https://doi.org/10.1016/j.jafr.2020.100076.

Andersson, H. and Treich, N. 2013. The Value of a Statistical Life, in: Handbook of Transport Economics. Edward Elgar, Cheltenham, UK, pp.396–424.

Angelov, A.G. and Ekström, M. 2017. Nonparametric estimation for self-selected interval data collected through a two-stage approach. *Metrika*, 80, pp.377–399. https://doi.org/10.1007/s00184-017-0610-7.

Baker, R. and Ruting, B. 2014. Environmental Policy Analysis: A Guide to Non-Market Valuation - Staff Working Paper. Productivity Commission, pp.45.

Bodah, B.W., Neckel, A., Stolfo Maculan, L., Milanes, C.B., Korcelski, C., Ramírez, O., Mendez-Espinosa, J.F., Bodah, E.T. and Oliveira, M.L.S. 2022. Sentinel-5P TROPOMI satellite application for NO2 and CO studies aiming at environmental valuation. *Journal of Cleaner Production*, 357, pp. 131960. https://doi.org/10.1016/j.jclepro.2022.131960.

Ciriacy-Wantrup, S.V. 1947. Capital Returns from Soil-Conservation Practices. *American Journal of Agricultural Economics*, 29, pp.1181–1196. https://doi.org/10.2307/1232747.

Colmer, J. 2020. What is the meaning of (statistical) life? Benefit–cost analysis in the time of COVID-19. *Oxford Review of Economic Policy*, 36, pp.S56–S63. https://doi.org/10.1093/oxrep/graa022.

Criado, C.O. and Veronesi, M. 2013. Parametric vs nonparametric dichotomous choice contingent valuation models: testingthe kernel estimator and its revealed performanc, in: Environmental Economics II. Presented at the SSES Anual Congress, University of Neuchâtel, Swizerland.

Cropper, M., Hammitt, J.K. and Robinson, L.A. 2011. Valuing Mortality Risk Reductions: Progress and Challenges. *Annual Review of Resource Economics*, 3, pp.313–336. https://doi.org/10.1146/annurev.resource.012809.103949.

Daniel, W.W. and Cross, C.L. 2013. Estimation, in: Biostatistics: A Foundation for Analysis in the Health Sciences,. Wiley, USA, pp. 958.

Dhungana, A.R. and Baral, B. 2016. Factors Affecting Willingness to Pay for Improved Water Supply System in Rural Tanahu, Nepal. *Janapriya Journal of Interdisciplinary Studies*, 5, pp.1–13. https://doi.org/10.3126/jjis.v5i0.17836.

DONRE 2021. Ho Chi Minh City's Environmental Quality Report of 2021.

Eiji, O., Masafumi, M., Phouphet, K. and Hiroshi, S. 2012. Measurement of Value of Statistical Life by Evaluating Diarrhea Mortality Risk due to Water Pollution in Laos and Vietnam. European Regional Science Association (ERSA), Louvain-la-Neuve, pp.1–5.

EPAVN V.E.P.A. 2023. Vietnam National Technical Regulation on Air Quality QCVN 05:2023.

Giolo, S.R. 2004. Turnbull's Nonparametric Estimator for Interval-Censored Data. Department of Statistics, Federal University of Parana, Brazil.

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

Haab, T.C. and Connell, K.E. 2002. Valuing Environmental and Natural Resources, New Horizons in Environmental Economics. Edward Elgar, UK, pp.352.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. 2019. Multivariate data analysis, Eighth edition. ed. Cengage, Andover, Hampshire.

Hammitt, J.K. 2000. Valuing Mortality Risk: Theory and Practice. *Environmental Science & Technology*, 34, pp.1396–1400. https://doi.org/10.1021/es990733n.

Ho Chi Minh City's Department of Health 2025. Hành trình 50 năm công tác dân số góp phần vào sự phát triển kinh tế - xã hội của Thành phố Hồ Chí Minh. Online available: http://medinet.hochiminhcity.gov.vn/ky-niem-50-nam-giai-phong-mien-nam-thong-nhat-dat-nuoc-3041975-3042025/hanh-trinh-50-nam-cong-tac-dan-so-gop-phan-vao-su-phat-trien-kinh-te-xa-hoi-cua-cmobile16645-73088.aspx (Accessed 11/3/25).

Hoevenagel, R. 1994. An Assessment of the Contingent Valuation Method, in: Pethig, R. (Ed.), Valuing the Environment: Methodological and Measurement Issues. Springer Netherlands, Dordrecht, pp.195–227. https://doi.org/10.1007/978-94-015-8317-6_8.

Hosmer, D.W., Lemeshow, S. and Sturdivant, R.X. 2013. Applied Logistic Regression, 3rd ed. John Wiley & Sons. https://doi.org/10.1002/9781118548387.

Hoyos, D. and Mariel, P. 2010. Contingent Valuation: Past, Present and Future. *Prague Economic Papers*, 19, pp.329–343. https://doi.org/10.18267/j.pep.380.

Hu, P., Zhou, Y., Zhou, J., Wang, G. and Zhu, G. 2022. Uncovering the willingness to pay for ecological red lines protection: Evidence from China. *Ecological Indicators*, 134, pp.108458. https://doi.org/10.1016/j.ecolind.2021.108458.

Hutchinson, W.G., Scarpa, R., Chilton, S.M. and McCallion, T. 2001. Parametric and Non-Parametric Estimates of Willingness to Pay for Forest Recreation in Northern Ireland: A Discrete Choice Contingent Valuation Study with Follow-Ups. *Journal of Agricultural Economics*, 52, pp.104–122. https://doi.org/10.1111/j.1477-9552.2001.tb00912.x.

IQAir 2024. Report of World Air Quality 2023. Online available: https://www.iqair.com/vi/newsroom/waqr-2023-pr (Accessed 7.25.25).

Junlin, R., Xiao, B., Xinyue, L. and Ziqian, P. 2024. Analysis of the factors influencing willingness to pay and payout level for watershed eco-compensation of the Huangbai river basin. *Water Supply*, 24, pp.1102–1116. https://doi.org/10.2166/ws.2024.058.

Karytsas, S., Polyzou, O. and Karytsas, C. 2019. Factors affecting willingness to adopt and willingness to pay for a residential hybrid system that provides heating/cooling and domestic hot water. *Renewable Energy*, 142, pp.591–603. https://doi.org/10.1016/j.renene.2019.04.108.

Kenkel, D. 2003. Using Estimates of the Value of a Statistical Life in Evaluating Consumer Policy Regulations. *Journal of Consumer Policy*, 26, pp.1–21. https://doi.org/10.1023/A:1022646013504.

Kniesner, T.J. and Viscusi, W.K. 2019. The Value of a Statistical Life. Oxford Research Encyclopedia of Economics and Finance (New York, NY, online edn, Oxford Academic, 29 Mar. 2018). https://doi.org/10.1093/acrefore/9780190625979.013.138. (Accessed 16 April 2026).

Le, T.N.H. and Bui, D.H. 2020. Willingness to pay for air quality improvement in Ho Chi Minh City, Vietnam. *The Journal of Agriculture and Development*, 19, pp.1–10. https://doi.org/10.52997/jad.5.06.2020.

Loan, T.T. 2018. More than 60 thousands people dead every year in Vietnam for air pollution. World Health Organization. Online available: https://www.who.int/vietnam/vi/news/detail/02-05-2018-more-than-60-000-deaths-in-viet-nam-each-year-linked-to-air-pollution (Accessed 27/7/2025).

Loureiro, M.L., Loomis, J.B. and Nahuelhual, L. 2004. A comparison of a parametric and a non-parametric method to value a non-rejectable public good. *Journal of Forest Economics*, 10, pp.61–74. https://doi.org/10.1016/j.jfe.2004.05.002.

McFadden, D. 1977. Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments. Cowles Foundation Discussion Papers, Cowles Foundation Discussion Papers.

Nguyen, C.T. and Le, H.T. 2019. A choice experiment to estimate willingness-to-pay for air quality improvements in Hanoi City: Results of a pilot study, in: ICSEED2019. Presented at the International conference on Social Economic and Environmental Issue in Development, National Economics University, Vietnam, Hanoi, Vietnam.

Nhung, N.T.T., Duc, V.T., Ngoc, V.D., Dien, T.M., Hoang, L.T., Ha, T.T.T., Khue, P.M., Truong, N.X., Thanh, N.T.N., Jegasothy, E., Marks, G.B. and Morgan, G. 2022. Mortality benefits of reduction fine particulate matter in Vietnam, 2019. *Frontiers in Public Health*, 10, pp. 1056370. https://doi.org/10.3389/fpubh.2022.1056370.

Paul, P., Pennell, M.L. and Lemeshow, S. 2013. Standardizing the power of the Hosmer-Lemeshow goodness of fit test in large data sets. *Statistics in Medicine*, 32(1), pp.67–80. https://doi.org/10.1002/sim.5525.

Perni, Á., Barreiro-Hurlé, J. and Martínez-Paz, J.M. 2021. Contingent valuation estimates for environmental goods: Validity and reliability. *Ecological Economics*, 189, pp.107144. https://doi.org/10.1016/j.ecolecon.2021.107144.

Phan, L. 2025. Ho Chi Minh City's air quality degradation, fine dust increasing. Tuoi Tre Online. Online available: https://tuoitre.vn/canh-bao-khan-chat-luong-khong-khi-tp-hcm-suy-giam-bui-min-tang-20251217110358159.htm (Accessed 7/4/2026).

Ranneby, B. and Yu, J. 2011. Estimation of WTP with Point and Self-selected Interval Responses. Research Report Centre of Biostochastics, pp. 1-11.

Sajise, A.J., Samson, J.N., Quiao, L., Sibal, J., Raitzer, D.A. and Harder, D. 2021. Contingent valuation of nonmarket benefits in project economic analysis; A guide to good practice. Asian Development Bank, Philipine. pp. 208. http://dx.doi.org/10.22617/TCS210514-2.

Singh, A.S. and Masuku, M., 2013. Sampling Techniques & Determination of Sample Size in Applied Statistics Research: An Overview. *International Journal of Economics, Commerce and Management*, 1, pp. 1-22.

Sundström, K. and Andersson, H., 2009. Swedish Consumers' Willingness to Pay for Food Safety - a Contingent Valuation Study on Salmonella Risk. Swedish National Road & Transport Research Institute, Sweden, pp.1-46.

Le, T. 2018. Ho Chi Minh City residents have an average of 9.68 years of education. Báo Người Lao Động Online. Online available: https://nld.com.vn/giao-duc-khoa-hoc/so-nam-hoc-tap-trung-binh-cua-nguoi-dan-tp-hcm-la-968-nam-20181205094105831.htm (Accessed 29/5/2026).

Tang, R., Zhao, J., Liu, Y., Huang, X., Zhang, Y., Zhou, D., Ding, A., Nielsen, C.P. and Wang, H. 2022. Air quality and health co-benefits of China's carbon dioxide emissions peaking before 2030. *Nature Communications*, 13, pp.1008. https://doi.org/10.1038/s41467-022-28672-3.

Thanh, B. 2025. By 2025: How much of Ho Chi Minh City's population will have a university degree or higher? Online available: https://thanhnien.vn/27-dan-so-tphcm-co-trinh-do-dai-hoc-tro-len-185251223214942669.htm (Accessed 31/5/2026).

Thormann, T.F. and Wicker, P., 2021. Willingness-to-Pay for Environmental Measures in Non-Profit Sport Clubs. *Sustainability*, 13, pp.2841. https://doi.org/10.3390/su13052841.

Trung, T.D.B. and Tri, D.Q. 2022. Application of the AERMOD Model to Evaluate the Health Benefits Due to Air Pollution from the Public Transport Sector in Ha Noi, Viet Nam. *Journal of Geoscience and Environment Protection*, 10, pp.13-33. https://doi.org/10.4236/gep.2022.103002.

Vietnam General Statistics Office 2025. Average income of a labor by locality divided by Province/City and Year. Average income of a labor by locality divided by Province/City and Year. Online available: https://www.nso.gov.vn/px-web-2/ (Accessed 3/9/2025).

Vincent Biausque 2012. The value of statistical life: A Meta Analysis. National Bureau of Economic Research, 1050 Massachusetts Avenue Cambridge, MA 02138, pp.1-24.

Viscusi, W.K., Aldy, J.E., 2003. The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World. *Journal of Risk and Uncertainty*, 27, 5–76. https://doi.org/10.1023/A:1025598106257.

Vu, T.X., Chon, L.Q., Vu, T.X. and Chon, L.Q. 2021. A Review on Current Status of Urban Air Pollution in Ho Chi Minh city and Ha Noi. *DTU Journal of Science and Technology*, 4, pp.45–53.

WHO 2021. WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide, World Health Organization. ed. World Health Organization, Geneva.

Woolley, N., Lövenich, A. and Ryan, D. 2015. Estimating the global economic cost of drowning. Online available: https://share.google/nA4rfx4iGRlAmLwYI.

World Bank 2021. Socio-Economic Costs and Human Impacts of Road Accidents in Azerbaijan. World Bank, Washington, DC. https://doi.org/10.1596/35986.

Xiong, K., Kong, F., Zhang, N., Lei, N. and Sun, C. 2018. Analysis of the Factors Influencing Willingness to Pay and Payout Level for Ecological Environment Improvement of the Ganjiang River Basin. *Sustainability*, 10, pp.2149. https://doi.org/10.3390/su10072149.

Yulianus, B. and Riaman, S. 2021. Willingness to pay of fishermen insurance using logistic regression model. Jurnal Matematika Integratif, pp. 15–21. https://doi.org/10.24198/jmi.v17.n1.32037.15-21.