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Factors Affecting Individuals' Willingness to Pay for the Reduction of Industrial Pollution: Empirical Findings from the Indian Himalayan Region

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ABSTRACT

The study aims to assess an individual's willingness to pay (WTP) to mitigate industrial pollution in the Indian Himalayan Region (IHR) and to analyse the role of socio-economic and psycho-social factors influencing WTP. Primary data for the study is collected from a critically polluted area of Byrnihat (Assam), India, by employing a double-bounded dichotomous choice (DBDC) method, and the data is analysed using descriptive statistics and a maximum likelihood estimation (MLE) method. The results revealed that the mean WTP amounts to INR 218 (USD 2.62) per household per month. About 73% of the respondents have expressed their WTP. Psycho-social factors such as awareness about environmental issues and knowledge about the advantages of a pollution-free environment influence the willingness of individuals to contribute. Education, income, and gender are among the key socio-economic factors that positively affect the monetary value of WTP. The study highlights the problem of industrial pollution, which has started affecting the fragile ecosystem of the IHR as well. Thus, research has been conducted to determine the importance of a clean and pollution-free environment to people residing near industrial units. The results underscore the urgency of enacting stringent environmental regulations that target neglected industrial clusters in the IHR.

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INTRODUCTION

Industrial pollution, which was limited to the plain regions of the Indian subcontinent, has now started deteriorating the environmental conditions of the IHR as well. The IHR consists of several Indian states, and it possesses a distinct and ecologically valuable asset. The region is well known for its picturesque mountain ranges, ancient cultural history, and wide range of plant and animal life. The rapid expansion of industrial activities in this region has become a concern for this delicate ecosystem, which has substantial effects on both the people that inhabit it and the environment (Kshetriya et al., 2021). It is worth mentioning that the Himalayas, which are generally considered to have a plethora of clean air and water, are slowly and gradually turning into polluting zones (Gajananda et al., 2005). A few studies have shown that both man-made and natural forces are responsible for the deteriorating environmental conditions in the area (R. Ganguly et al., 2021; Panwar et al., 2020). Air pollution has risen substantially due to the rapid growth of industries in the Himalayas (Hassan et al., 2023). The Central Pollution Control Board of India (CPCB), using the comprehensive environmental pollution index (CEPI), has listed five towns in IHR as polluted areas, out of which three are from Himachal

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Pradesh (namely Baddi, Parwanoo, and Kala Amb) and one each from Uttarakhand (Udham Singh Nagar) and Assam (Byrnihat). CEPI score reflects the environmental status of industrial clusters by providing the aggregate value of air, water and land pollution levels. Byrnihat, an industrial town on the Guwahati-Shillong highway, is one such region with the highest CEPI score of 78.31 (CPCB, 2013). The presence of a large number of industries and the dumping of industrial and household waste into a nearby drain is a significant factor in such a high CEPI score. Coke, cement manufacturing, and chemical industries are among the significant contributors to pollution in this region, and this is causing health, water, sewage, and air quality issues for the nearby community.

The term WTP describes a person's willingness to make a financial contribution or take particular actions to address environmental problems and safeguard natural resources. Ciriacy-Wantrup (1947) initially theorised the Contingent Valuation Method (CVM) as a technique for extracting the market valuation of a non-market good, such as pollution. The utilisation of this approach was initially employed in the assessment of the economic worth of outdoor recreational activities. Empirical studies assessing the WTP have extensively used CVM techniques. To determine people's WTP for carbon offsets from train travel, Lim & Yoo (2014) used the DBDC approach. Chien et al. (2005) created a generic model to assess the health benefits of better air quality using the CVM and dichotomous choice (DC) techniques. Shono et al. (2014) and Zalejska-Jonsson (2014) carried out CVM surveys to assess Indonesian public WTP for healthcare services and to evaluate the WTP for green flats in Sweden, respectively. Similarly, El-Fadel & Massoud (2000) utilised the CVM to conduct a health-based economic assessment, while Y. Wang et al. (2017) assessed people's WTP to avoid living near nuclear power plants in China. Many studies, like those by Ouyang et al. (2019), Sun et al. (2016), Martín-López et al. (2007), and Ray et al. (2023), estimated an individual's WTP and how variables like age, income, and family size significantly affect the amount of WTP.

A number of researchers have conducted estimations regarding individuals' WTP for environmental services pertaining to diverse resources and have concluded that the amount of WTP can certainly be considered as a cost of pollution for the respective respondents (Ahsan et al., 2021; Ain et al., 2021; Hadker et al., 1997; Ouyang et al., 2019; Rafique et al., 2022; Tamang & Jana, 2017; Zalejska-Jonsson, 2014). A wide range of factors that go beyond purely economic ones affect WTP perception, such as socio-cultural, demographic, and environmental factors, which can have a significant impact on an individual's attitude toward environmental conservation and willingness to participate in actions to reduce pollution (García-Llorente et al., 2016). Though industries have a huge impact on a nation's socio-economic development, those primarily relying on antiquated methods and equipment cause pollution that has a severe effect on the environment and general well-being (Kamal et al., 2016; Preet et al., 2022; Ravindra & Mor, 2019; Shah et al., 2022). Industrial activities have raised concerns about all forms of pollution and thus turn out to be detrimental for human well-being as they have increased health care expenditure (Ahmad et al., 2018; Nguyen et al., 2021; Shen et al., 2021; Zhang et al., 2020). At the macroeconomic level, pollution has also been observed to result in a decline in a nation's income as a consequence of decreased production and efficiency, ultimately leading to a reduction in savings (Liu et al., 2020). In India in 2019, air pollution alone was responsible for 18% of all fatalities (Kaushal, 2021). To support the National Clean Air Programme (NCAP) of India, infrastructure for environmental sustainability, more economic autonomy for municipal bodies, and periodic updates on emission norms are necessary (T. Ganguly et al., 2020). One of the main causes of the continuous discharge of pollution, particularly in the IHR, is the ever-increasing industrialisation and anthropogenic interferences (Chandra & Kumar, 2021; Chu & Karr, 2017). The situation is worst for industrial workers, as the untreated industrial pollution and presence of dust and smoke particles in the air have a significant negative impact on their health and, as a result, their productivity at work (Fakher et al., 2018). Understanding people's perceptions of WTP with regards to pollution is crucial since it can reveal how much local communities are aware of and concerned about environmental deterioration. Hence, it is imperative to conduct an analysis of the economic ramifications of industrial pollution on individuals and evaluate their inclination to allocate funds for enhanced air quality and projects related to sustainable development and pollution reduction (Verbič & Slabe-Erker, 2009).

While several studies have investigated environmental perceptions and WTP in various contexts, it is limited to major cities and mega-industrial hubs only, and research focusing specifically on the IHR is limited. The region's unique socio-cultural context and ecological significance necessitate a dedicated examination of how individuals in the IHR perceive industrial pollution and their willingness to financially contribute towards its avoidance. Thus, it is important to quantify the cost of industrial pollution in terms of the WTP of such blossoming industrial clusters of IHR. The present research uses the DBDC approach based on CVM to simulate people's responses based on how they would react in hypothetical situations (Galati et al., 2022). The MLE method is applied to assess the mean monetary value of WTP to mitigate industrial pollution, along with the role of socio-economic factors (such as age, education, gender, income, etc.) and psycho-social factors (such as attitude, knowledge, and behaviour control) in influencing the value of WTP. This approach yields the most conservative results in experimental research when compared to the other widely used formats: single-bounded dichotomous choice (SBDC) and open-ended (OE) formats (Moradi & Rashidian, 2015; Shafie et al., 2014). The majority of existing research on industrial pollution management primarily focuses on the micro-level and policy aspects. In contrast, this study utilises microdata and provides a microfoundation by examining the possible barriers that stop people from participating in WTP and suggesting some policy measures that may contribute to environmental protection in the unexplored and critically polluted IHR.

MATERIALS & METHODS

The primary data was collected from the population of Byrnihat living in the core area, that is, within a 3-kilometer radius of industrial units. It has been observed that mostly industrial pollution has a significant effect within 3 km of industrial units (Swarup et al., 1998).The survey was carried out in the months of January and February of 2023, and the respondents were selected using a custom random selection process, and 405 questionnaires were found to be valid out of the total 424 questionnaires distributed. Applying Cochran statistics, the intended sample size for this investigation was 384. However, an additional 10% of this size is considered to rule out any prejudice. One potential limitation of assessing WTP is its susceptibility to starting-point bias. Starting-point bias is generally associated with the tendency that respondents will usually say "yes" to the question, regardless of its content. When respondents are unsure about the significance of a thing (e.g., a clean and pollution-free environment), they will turn to an "anchor" as a reference point to make a value assessment, and henceforth, true WTP value gets trapped due to the anchoring effect. To address this concern, participants were randomly allocated to one of three distinct starting offers using the DBDC approach, with initial values of 100, 175, and 250.

This research employs descriptive statistics and a MLE method with spikes, as it assumes a non-zero probability of a zero WTP response while assessing the role of factors responsible for WTP. MLE method provides better results than the traditional OLS (Ordinary Least Square) model, while dealing with the censored data and parameter estimation is done more accurately as the former method allows more flexibility and can accommodate the problems of heteroscedasticity, even after including the covariates in a model. Respondents were asked whether they would be willing to pay a certain amount per month if the government or some other body took the initiative to drastically cut industrial pollution in their area. To eliminate biases and estimate the true WTP, the DBDC method is used, where three different monetary amounts are presented to a respondent: X_1 for the initial amount, X_2 if the respondent answers "yes," and X_3 for a "no" answer (where $X_3 < X_1 < X_2$). If a person says "yes" twice, then their WTP is at least X_2, and if they say "no" twice, then their WTP is at least X_3. This is where the DBDC approach differs from the single-bounded CVM. "Yes-yes", "yes-no," "no-yes," and "no-no" are four possible answers. The binary-valued indicator variables are, correspondingly, K_i^{YY}, K_i^{YN}, K_i^{NY}, and K_i^{NN}.

K_i^{YY} (the response of $_i^{th}$ sample is "yes-yes")
K_i^{YN} (the response of $_i^{th}$ sample is "yes-no")
K_i^{NY} (the response of $_i^{th}$ sample is "no-yes")
K_i^{NN} (the response of $_i^{th}$ sample is "no-no")

The random variable WTP is denoted and is characterised by its cumulative distribution function (cdf), denoted as $G_C(X; \theta)$. In this context, X represents the bid value, while θ represents the parameter that needs to be estimated. X_i represents the first bid, X_i^u (where $X_i < X_i^u$) denotes the subsequent bid following an affirmative response to the initial offer, and X_i^d signifies the subsequent bid following a negative response to the local bid. The log-likelihood function is expressed in the following form:

$$\ln L = \sum\{K_i^{YY} \ln[1-G_C(X_i^u;\theta)]+K_i^{YN} \ln[G_C(X_i^u;\theta)-G_C(X_i;\theta)] \quad i=1+K_i^{NY} \ln[G_C(A_i;\theta)-G_C(X_i^d;\theta)]+K_i^{NN} \ln G_C(X_i^d;\theta)\} \tag{1}$$

By expressing the function $1 - G_C(.)$ as the logistic cumulative distribution function (cdf) and using the parameters θ = (a, b), the following formulation is obtained:

$$G_C (X_i;\theta) = [1 + \exp(a - b_X]^{-1} \tag{2}$$

Let C+ represent the average WTP when C has the potential to take on both positive and negative values. The calculation of the mean WTP can be expressed as C+ = a/b. When confronted with a lack of responses, the spike model proposed by Hu (2006) and Kriström (1997) is employed. The spike model assigns positive probability to the zero WTP value as well. This model is suitable, where a significant number of zero responses are recorded while assessing the mean WTP (Del Saz-Salazar & Garcia-Menendez, 2001). The participants who provided a "no-no" response were subsequently asked a follow-up question to differentiate between genuine zero WTP samples and positive ones. K_i^{NN} can be categorised into K_i^{NNY} and K_i^{NNN}. The log-likelihood function for the spike model can be expressed as follows:

$$\ln L = \sum \{K_i^{YY} \ln[1-G_C (X_i^u ;\theta)]+K_i^{YN} \ln[G_C (X_i^u ;\theta)-G_C (X_i ;\theta)]+K_i^{NY} \ln[G_C(X_i;\theta)-G_C(X_i^d;\theta)]+ K_i^{NNY} [\ln G_C (X_i^d ;\theta)-G_C (0 ;\theta)]+K_i^{NNN} [G_C (0 ;\theta)]\} \tag{3}$$

The spike is mathematically described as the inverse of the sum of one plus the exponential of a, denoted as $[1 + \exp(a)]^{-1}$. Furthermore, the average mean WTP can be determined using the equation:

$$C^+ = (1/b)\ln[1 + \exp(a)] \tag{4}$$

Here, b is the coefficient of bid value, and "a" is the constant term. A total of 405 investigations are distributed equally among the three bidding sets based upon the income level of the respondents. For example, to elicit WTP from the respondents from lower income groups, they were asked whether they would be willing to pay INR 100 on a monthly basis, and in return, efforts would be made to reduce industrial pollution in their area. Based upon the response received for the initial bid value, the next bid value was either doubled to INR 200 (for a positive response) or halved to INR 50 (for a negative response) in the follow-up question using the DBDC approach. The results of the DBDC approach are shown in Table 1 for a fictitious respondent with a true WTP i.e., WTP_i.

RESULTS & DISCUSSION

The distribution of WTP responses is shown in Table 2. There were a total of three defined bidding combinations: INR (50/100/200), INR (90/175/350), and INR (125/250/500). These bid values were distributed among the sample respondents based on their income level. It can be inferred from Table 2 that as each bid increases, the number and proportion of "yes-yes" responses decrease, accompanied by a rapid increase in the proportion of "no-no-no" responses. It can be inferred from Table 2 that 73% of the respondents show WTP to mitigate industrial pollution.

About 110 respondents were not willing to contribute any amount, and this has been recorded as negative WTP reactions. The causes of such responses were further examined in the study and presented in Table 3. 27.16% of respondents state their unwillingness to pay more for an industrial-pollute-free environment. Due to low family incomes, 20.91% of respondents who had zero WTP were considered to be in the category of true zero responses. Additionally, when it came to protest reactions, 26.36% said the industrial units should pay the fees. One in five

Table 1. Estimating Individual's WTP with Different Monetary Amounts Offered in a DBDC Survey.

Initial Question Response	**Follow Up Questions Response**	
	Yes	No
Yes	$WTP_i > X_2$	$X_2 > WTP_i > X_1$
No	$X_1 > WTP_i > X_3$	$WTP_i < X_3$

Source: Author's own calculation

Table 2. Response Distribution to Three Different Bid Values Used in the DBDC Method.

Bid Values	**Sample**	**Yes-Yes Values (in %)**	**Yes-No Values (in %)**	**No-Yes Values (in %)**	**No-No-Yes Values (in %)**	**No-No-No Values (in %)**
50/100/200	135	27 (20)	43 (32)	21 (16)	18 (13)	26 (19)
90/175/350	135	26 (19)	39 (29)	19 (14)	15 (11)	36 (27)
125/250/500	135	22 (16)	34 (25)	16 (12)	15 (11)	48 (36)
Total	405	75 (18)	116 (29)	56 (14)	48 (12)	110 (27)

Source: Author's own calculation

Table 3. Results of the Description of Non-Positive Responses Received for WTP

Description	**Type**	**No.(%)**
No improvement is required in the environment quality	Genuine response	2 (1.82)
Willing to contribute but not able to due to restricted income		23 (20.91)
Polluting industry should be responsible for this.	Protest response	29 (26.36)
Government should take initiative regarding this.		17 (15.45)
Consumers of polluting industries should be held accountable.		4 (3.64)
No serious efforts were taken by the responsible agencies in the past.		13 (11.82)
Taxes are already at high level		19 (17.27)
Others		3 (2.73)
Total		**110 (100)**

Source: Author's own calculation

respondents said the government ought to curb industrial pollution. 17.27% stated they had paid all their taxes and fees and would not pay more. Those who claimed “zero” may have a positive WTP if their economic conditions improve or the environment worsens, but protesters probably don’t.

The descriptive statistics of the sample variables are defined and analysed in Table 4. The average family size is 2.05, and the average age of the respondents lies between 30 and 45 years. This working-age population can provide valid insights into the problem of industrial pollution in the IHR. 73.48% of the participants demonstrated awareness of the existing environmental issues in Byrnihat, while 68.8% of them possessed information regarding the beneficial effects of a pollution-free environment. 79.2% of the respondents opined that undertaking methods to improve the environmental conditions will not impose any difficulties on their lifestyles, which

Table 4. Results of Descriptive Statistics of Selected Socio-Economic and Psycho-Social Indicators and Three Key Variables: Attitude, Knowledge and Behaviour Control

Category	Variables	Description	Mean	S.D.	Min	Max
Socio-Economic Indicators	Gender	Male = 1, Female = 0	0.52	0.49	0	1
	Education	Dummy variable Graduate = 1	0.38	0.47	0	1
	Age	Age of the Respondents (in years) Less than 30 = 1 Between 30 – 45 = 2 Between 45 – 60 = 3 60 and above = 4	1.77	0.99	1	4
	Family size	Number of household members	2.05	1.06	1	10
	Income	Monthly Income (in INR) : under 10,000 = 1, 10,000 - 25,000 = 2, 25000 – 50,000 = 3, 50,000 and above = 4	1.88	1.10	1	4
	Disease	Dummy variable - Anyone in the family suffering from disease caused due to industrial pollution = 1	0.63	0.48	0	1
	Child	Having a child under 12 years of age = 1 No Child = 0	0.52	0.46	0	1
Psycho-social Indicators	Attitude	Awareness about environmental issues. Range is from 1 to 5 using Likert scale, where 1 is for strongly disagree and 5 is for strongly agree.	3.63	0.61	1	5
	Knowledge	Knowledge about the impact of industrial pollution-free environment. Range is from 1 to 5 using Likert scale, where 1 is for strongly disagree and 5 is for strongly agree.	3.44	0.95	1	5
	Behavioural control	Considering improving environmental conditions not difficult. Range is from 1 to 5 using Likert scale, where 1 is for strongly disagree and 5 is for strongly agree.	3.96	1.03	1	5

Source: Author’s own calculation

Table 5. Results of the MLE Method using Spikes to Explain the Determinants of WTP.

Variables	Model without covariates	Model with covariates
Constant	−0.08 (−0.99)	−1.36 (−3.20)***
Bid	−0.39 (12.19)***	−0.42 (13.54)***
Gender		0.19 (2.51)**
Income		0.21(2.01)**
Education		0.87 (2.01)**
Age		−0.17 (−0.19)
Family Size		−0.04 (−0.41)*
Disease		0.18 (0.03)
Child		0.31 (0.41)
Attitude		0.42 (1.67)***
Knowledge		0.28 (2.05)**
Behavioural control		0.15 (0.38)
Spike	0.26	0.28 (21.27)***
Mean WTP[1]	218.10	236.80
Log-Likelihood	−1011.48	−992.98
Wald Statistic	492.60 (0.000)	429.78 (0.000)

Source: Author's own calculation[2]

[1] At the time of data analysis USD 1 = INR 83.24.

[2] The t-values, which have been calculated using the analytic second derivatives of the log-likelihood function, are presented within parenthesis. The symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively. The null hypothesis posits that all parameters exhibit a collective value of zero, with the p-value associated with the statistic being presented between parentheses.

highlights that respondents' behaviour will be quite optimistic about such change. The response to certain psycho-social questions serves as the foundation for the independent variable. Using a scale ranging from 1 (strongly disagree) to 5 (strongly agree), respondents rated their level of general awareness regarding environmental issues. The answer to this question determines the variable "attitude." The notions of "knowledge" explain understanding the impact of industrial pollution on daily life, and "behaviour control" exhibits how respondents behave towards the process of improving environmental quality.

The results of the MLE method with the spikes are reported in Table 5. The statistical significance of the coefficient of the bid value was observed at a significance level of 1%. As anticipated, the probability of receiving a positive response drops with an increase in the size of the bid. The estimations in the third column present results that incorporate confounders and variables that have the potential to influence the probability of receiving a "yes" response. The covariates include gender, income, age, education, family size, disease, and children. Results found a positive and statistically significant attitude coefficient (representing environmental consciousness) at the 1% level of significance. Knowledge regarding the pollution-free environment also positively impacts respondents' WTP. Household income also had a beneficial effect on WTP. Individuals with higher educational attainment exhibit a greater propensity to pay for a pollution-free environment. The gender of the respondent is also statistically significant, as male respondents are willing to pay more for this cause. The results also indicated that respondents with smaller families were more inclined to participate in the WTP process for a pollution-free environment.

Consistent with economic limitations, the results were reasonable, and the negative regression coefficient for the bid value indicated that respondents were willing to pay less as the bid value increased. Using the Wald statistic, the estimated equation was statistically significantly different from zero at the 1% level. The estimated value for the spike is 0.26 in the model without covariates and 0.28 in the model with covariates. These estimates closely align with the proportion of zero responses indicated in Table 3. Furthermore, by using the equation:

Image 1. Umtru river in Byrnihat

Image 2. Industrial unit in Byrnihat

Image 3. Some sources of livelihood in Byrnihat

Image 4. Industrial unit polluting the air.

Image 5. Polluted Umtru river under Guwahati-Shillong national highway.

Image 6. Movement of heavy vehicles in the area.

$C^+ = (1/b)\ln[1 + \exp(a)]$, the mean WTP was estimated to be INR 218.10, or USD 2.62, without considering covariance, and INR 236.80, or USD 2.84, when covariance was considered, per household per month.

Residents of Byrnihat expressed apprehension regarding the escalating cost of living because of the activities carried out by industrial establishments. They acknowledged the contingent market and expressed their willingness to make a substantial contribution. The level of willingness differs based on certain individual traits, such as gender, income, education, family size, attitude, and knowledge. Respondents possess knowledge regarding the issues of industrial pollution and its detrimental effects on the well-being of humans. They directly correlate their concerns about the quality of the environment with their concerns about ecological problems and their understanding of a pollution-free environment. This factor has a substantial impact on a resident's WTP. Those who possess knowledge about environmental issues and the good externalities that will result from a pollution-free world are more inclined to pay the extra cost, as they can better utilize it. Below are the images captured during the data collection from the research area:

The DBDC approach is incentive-compatible, like market bargaining. Simulating the problem helps respondents communicate their ideas realistically. This model shows inhabitants' true WTP using a random utility model, and the results are in line with several studies conducted in different regions (Borzino et al., 2020; Kim et al., 2020; Ku et al., 2009). The random utility model allows the respondent to give preference to one option over another, depending on the utility function. It is reasonable to assert that in forthcoming studies, the utilisation of the DBDC technique along with the MLE method has the potential to serve as a promising technique for eliciting WTP in the context of acquiring public WTP data for a proposed project. Though the DBDC approach helps in obtaining estimates of WTP as close as possible to the actual data, this paper still has some shortcomings. Environmental awareness and knowledge of pollution-free benefits were challenging to quantify. There could be many other social and economic variables that affect an individual's WTP. To address these limitations, further research and analysis are necessary.

CONCLUSION

The objective of this research was to assess the mean value of WTP to mitigate industrial pollution and the role of socio-economic and psycho-social factors that influence WTP. The primary data for this study was collected from the inhabitants of Byrnihat, Assam, situated in the IHR and formally classified as a critically polluted area by the CPCB of India. This study utilises the CVM and eliminates biases by employing the DBDC method. Specifically, three separate initial bid amounts with their corresponding values have been used to calculate the WTP for an improved environmental condition. The findings of this study suggest that the MLE method, when combined with the spikes, demonstrates a strong fit to the data under investigation. Apart from the bid variable, the primary influential socio-economic factors identified by the model were gender, income, education, and family size. Whereas, psycho-social factors such as attitude and knowledge also have a significant and positive impact on the amount of WTP. Respondents who have a family member with a disease are also willing to pay more for a pollution-free environment. The estimated mean WTP amounts to INR 218.10, or USD 2.62, per household per month in the IHR region to tackle industrial pollution. This amount can certainly be considered as a cost of industrial pollution for the residents and could act as a strong foundation for policymaking.

Based on the findings of this investigation, a subsequent policy proposal can be recommended. Despite the economic constraints, a major chunk of respondents are willing to pay for a cleaner and pollution-free environment. This indicates that there is a need to implement pollution abatement technology by industrialists with the support of the government. Though various efforts have been undertaken by the Union government of India by formulating laws and acts such as Pollution Abatement Policy 1992, National Environment Policy 2006, Clean India Mission 2014, and identification of Critically Polluted Areas (CPAs) by the CPCB, so far none of the programmes have realized their intended objectives. With greater awareness, novel strategies can be made that might substantially boost industrialists' incentives to behave in ways that are good for the environment and social welfare. It is very important that information about industrial pollution gets out to the public at the right time, and it is also important to hold regular legal public meetings so that people can share their thoughts on environmental issues.

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The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

REFERENCES

Ahmad, M., Khan, A. W., Mardan, U., Rahman, Z. U., Khan, Z., & Khan, M. N. (2018). Impact of Environmental Quality Variables and Socio-Economic Factors on Human Health: Empirical Evidence from China. *Pollution*, *4*(4), 571–579. https://doi.org/10.22059/poll.2018.252214.391

Ahsan, M. N., Hadiujjaman, S., Islam, M. S., Nasrin, N., Akter, M., Parvin, G. A., & Hossain, M. S. (2021). Willingness to pay for improved safe drinking water in a coastal urban area in Bangladesh. *Water Policy*, *23*(3), 633–653. https://doi.org/10.2166/wp.2021.031

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), 6611–6618. https://doi.org/10.1007/s11356-020-11023-4

Borzino, N., Chng, S., Mughal, M. O., & Schubert, R. (2020). Willingness to pay for urban heat island mitigation: A case study of Singapore. *Climate*, *8*(8), 1–26. https://doi.org/10.3390/CLI8070082

Chandra, P., & Kumar, J. (2021). Strategies for developing sustainable tourism business in the Indian Himalayan Region: Insights from Uttarakhand, the Northern Himalayan State of India. *Journal of Destination Marketing and Management*, *19*(December 2020), 100546. https://doi.org/10.1016/j.jdmm.2020.100546

Chien, Y. L., Huang, C. J., & Shaw, D. (2005). A general model of starting point bias in double-bounded dichotomous contingent valuation surveys. *Journal of Environmental Economics and Management*, *50*(2), 362–377. https://doi.org/10.1016/j.jeem.2005.01.002

Chu, E. W., & Karr, J. R. (2017). Environmental Impact: Concept, Consequences, Measurement. *Reference Module in Life Sciences*, 1–22. https://doi.org/10.1016/b978-0-12-809633-8.02380-3

Ciriacy-Wantrup, S. V. (1947). Capital Returns from Soil-Conservation Practices. *Journal of Farm Economics*, *29*(4), 1181–1196. https://doi.org/https://doi.org/10.2307/1232747

CPCB. (2013). *Action Plan for Integrated Industrial Area, Rudrapur, Udham SIngh Nagar, Uttarakhand*. https://ueppcb.uk.gov.in/files/Doc004_1.pdf

Del Saz-Salazar, S., & Garcia-Menendez, L. (2001). Willingness to pay for environmental improvements in a large city. *Environmental and Resource Economics*, *20*(2), 103–112. https://doi.org/10.1023/A:1012624211878

El-Fadel, M., & Massoud, M. (2000). Particulate matter in urban areas: Health-based economic assessment. *Science of the Total Environment*, *257*(2–3), 133–146. https://doi.org/10.1016/S0048-9697(00)00503-9

Fakher, H. A., Ahmadian, M., Abedi, Z., & Shaygani, B. (2018). Bayesian Econometrics Approach in Determining of Effecting Factors on Pollution in Developing Countries (based on Environmental Performance Index). *Pollution*, *4*(3), 447–457. https://doi.org/10.22059/poll.2018.243987.335

Gajananda, K., Kuniyal, J. C., Momin, G. A., Rao, P. S. P., Safai, P. D., Tiwari, S., & Ali, K. (2005). Trend of atmospheric aerosols over the north western Himalayan region, India. *Atmospheric Environment*, *39*(27), 4817–4825. https://doi.org/10.1016/j.atmosenv.2005.01.038

Galati, A., Migliore, G., Thrassou, A., Schifani, G., Rizzo, G., Adamashvili, N., & Crescimanno, M. (2022). Consumers' Willingness to Pay for Agri-Food Products Delivered with Electric Vehicles in the Short Supply Chains. *FIIB Business Review*, *12*(2), 193–207. https://doi.org/https://doi.org/10.1177/23197145221112743

Ganguly, R., Sharma, D., Kumar, P., & Gurjar, B. R. (2021). Dispersion Modeling of Air Pollutants in a Hilly City in India. *Journal of Hazardous, Toxic, and Radioactive Waste*, *25*(2), 1–11. https://doi.org/10.1061/(asce)hz.2153-5515.0000574

Ganguly, T., Selvaraj, K. L., & Guttikunda, S. K. (2020). National Clean Air Programme (NCAP) for Indian cities: Review and outlook of clean air action plans. *Atmospheric Environment: X*, *8*, 100096. https://doi.org/10.1016/j.aeaoa.2020.100096

García-Llorente, M., Castro, A. J., Quintas-Soriano, C., López, I., Castro, H., Montes, C., & Martín-López, B. (2016). The value of time in biological conservation and supplied ecosystem services: A willingness to give up time exercise. *Journal of Arid Environments*, *124*, 13–21. https://doi.org/10.1016/j.jaridenv.2015.07.004

Hadker, N., Sharma, S., David, A., & Muraleedharan, T. R. (1997). Willingness-to-pay for borivli national park: Evidence from a contingent valuation. *Ecological Economics*, *21*(2), 105–122. https://doi.org/10.1016/S0921-8009(96)00094-8

Hassan, M. A., Mehmood, T., Liu, J., Luo, X., Li, X., Tanveer, M., Faheem, M., Shakoor, A., Dar, A. A., & Abid, M. (2023). A review of particulate pollution over Himalaya region: Characteristics and salient factors contributing ambient PM pollution. *Atmospheric Environment*, *294*(October 2022), 119472. https://doi.org/10.1016/j.atmosenv.2022.119472

Hu, W. (2006). Use of Spike Models in Measuring Consumers' Willingness to Pay for Non-GM Oil. *Journal of Agricultural and Applied Economics*, *38*(3), 525–538. https://doi.org/10.1017/s1074070800022598

Kamal, A. K. I., Ahmed, F., Hassan, M., Uddin, M. K., Hossain, S. M., & 1. (2016). Characterization of Textile Effluents from Dhaka Export Processing Zone (DEPZ) Area in Dhaka, Bangladesh. *Pollution*, *2*(2), 153–161. https://doi.org/10.7508/pj.2016.0

Kaushal, H. (2021). The economic and health cost of Air pollution. In *Arun Duggal Centre for Clean Air* (Number October, bll 1–5). Indian Institute of Technology Delhi. https://cerca.iitd.ac.in/uploads/Letter/1633672611CERCA IITD Newsletter _ October.pdf

Kim, S. M., Kim, J. H., & Yoo, S. H. (2020). Households' willingness to pay for substituting natural gas with renewable methane: A contingent valuation experiment in south korea. *Energies*, *13*(12). https://doi.org/10.3390/en13123082

Kriström, B. (1997). Spike Models in Contingent Valuation. *American Journal of Agricultural Economics*, *79*(3), 1013–1023. https://doi.org/10.2307/1244440

Kshetriya, D., Warjri, C. D., Kumar Chakrabarty, T., & Ghosh, S. (2021). Assessment of heavy metals in some natural water bodies in Meghalaya, India. *Environmental Nanotechnology, Monitoring and Management*, *16*(January), 100512. https://doi.org/10.1016/j.enmm.2021.100512

Ku, S. J., Yoo, S. H., & Kwak, S. J. (2009). Willingness to pay for improving the residential waste disposal system in Korea: A choice experiment study. *Environmental Management*, *44*(2), 278–287. https://doi.org/10.1007/s00267-009-9325-5

Lim, H. J., & Yoo, S. H. (2014). Train travel passengers' willingness to pay to offset their CO2 emissions in Korea. *Renewable and Sustainable Energy Reviews*, *32*, 526–531. https://doi.org/10.1016/j.rser.2014.01.010

Liu, T., Pan, S., Hou, H., & Xu, H. (2020). Analyzing the environmental and economic impact of industrial transfer based on an improved CGE model: Taking the Beijing–Tianjin–Hebei region as an example. *Environmental Impact Assessment Review*, *83*(38). https://doi.org/10.1016/j.eiar.2020.106386

Martín-López, B., Montes, C., & Benayas, J. (2007). The non-economic motives behind the willingness to pay for biodiversity conservation. *Biological Conservation*, *139*(1–2), 67–82. https://doi.org/10.1016/j.biocon.2007.06.005

Moradi, N., & Rashidian, A. (2015). Willingness to Pay for Quality-Adjusted Life Years In Patients With Diabete. *Value in Health*, *18*(7), A617. https://doi.org/10.1016/j.jval.2015.09.2151

Nguyen, T. H. H., Elmagrhi, M. H., Ntim, C. G., & Wu, Y. (2021). Environmental performance, sustainability, governance and financial performance: Evidence from heavily polluting industries in China. *Business Strategy and the Environment*, *30*(5), 2313–2331. https://doi.org/10.1002/bse.2748

Ouyang, X., Zhuang, W., & Sun, C. (2019). Haze, health, and income: An integrated model for willingness to pay for haze mitigation in Shanghai, China. *Energy Economics*, *84*, 104535. https://doi.org/10.1016/j.eneco.2019.104535

Panwar, P., Prabhu, V., Soni, A., Punetha, D., & Shridhar, V. (2020). Sources and health risks of atmospheric particulate matter at Bhagwanpur, an industrial site along the Himalayan foothills. *SN Applied Sciences*, *2*(4), 1–12. https://doi.org/10.1007/s42452-020-2420-1

Preet, S., Chopra, S., & Gulati, A. (2022). Impact of sustainable development on economic growth: Evidence from OECD countries. *JIMS8M The Journal of Indian Management & Strategy*, *27*(2), 54–61. https://doi.org/10.5958/0973-9343.2022.00014.x

Rafique, M. Z., Sun, J., Larik, A. R., & Li, Y. (2022). Assessment of Willingness to Pay for Pollution Prevention, Health and Happiness: A Case Study of Punjab, Pakistan. *Frontiers in Public Health*, *10*(June). https://doi.org/10.3389/fpubh.2022.825387

Ravindra, K., & Mor, S. (2019). Distribution and health risk assessment of arsenic and selected heavy metals in Groundwater of Chandigarh, India. *Environmental Pollution*, *250*, 820–830. https://doi.org/10.1016/j.envpol.2019.03.080

Ray, M., Ryngnga, P. K., & Chetia, P. (2023). Willingness to pay and its determinants for improved solid waste management: a case study. *International Journal of Environment and Waste Management*, *31*(1), 119–134. https://doi.org/10.1504/IJEWM.2023.129729

Shafie, A. A., Lim, Y. W., Chua, G. N., Azmi, M., & Hassali, A. (2014). Exploring the willingness to pay for a quality-adjusted life-year in the state of Penang, Malaysia. *ClinicoEconomics and Outcomes Research*, *6*, 473–481. https://doi.org/10.2147/CEOR.S67375

Shah, S. N., Manzoor, S., & Asim, M. (2022). Impact of Industrial Pollution on Our Society. *Pakistan Journal of Science*, *73*(1), 222–229. https://doi.org/10.57041/pjs.v73i1.646

Shen, J. S., Wang, Q., & Shen, H. P. (2021). Does Industrial Air Pollution Increase Health Care Expenditure? Evidence From China. *Frontiers in Public Health*, *9*(June), 1–9. https://doi.org/10.3389/fpubh.2021.695664

Shono, A., Kondo, M., Ohmae, H., & Okubo, I. (2014). Willingness to pay for public health services in rural Central Java, Indonesia: Methodological considerations when using the contingent valuation method. *Social Science and Medicine*, *110*, 31–40. https://doi.org/10.1016/j.socscimed.2014.03.025

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/10.1016/j.enpol.2016.02.025

Swarup, D., Dwivedi, S. K., Dey, S., & Ray, S. K. (1998). Fluoride intoxication in bovines due to industrial pollution. *Indian Journal of Animal Sciences*, *68*(7), 605–608.

Tamang, P., & Jana, S. K. (2017). Willingness to Pay for Improved Water Services: A Case of Darjeeling, India. *Asian Journal of Water, Environment and Pollution*, *14*(2), 51–59. https://doi.org/10.3233/AJW-170015

Verbič, M., & Slabe-Erker, R. (2009). An econometric analysis of willingness-to-pay for sustainable development: A case study of the Volčji Potok landscape area. *Ecological Economics*, *68*(5), 1316–1328. https://doi.org/10.1016/j.ecolecon.2008.09.002

Wang, Y., Sun, M., & Song, B. (2017). Public perceptions of and willingness to pay for sponge city initiatives in China. *Resources, Conservation and Recycling*, *122*, 11–20. https://doi.org/10.1016/j.resconrec.2017.02.002

Zalejska-Jonsson, A. (2014). Stated WTP and rational WTP: Willingness to pay for green apartments in Sweden. *Sustainable Cities and Society*, *13*, 46–56. https://doi.org/10.1016/j.scs.2014.04.007

Zhang, M., Sun, X., & Wang, W. (2020). Study on the effect of environmental regulations and industrial structure on haze pollution in China from the dual perspective of independence and linkage. *Journal of Cleaner Production*, *256*, 120748. https://doi.org/10.1016/j.jclepro.2020.120748