Particulate matter 2.5 pollution, perception, and mental stress

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ABSTRACT

Multivariate mediation analyses were used to relate perceptions of particulate matter 2.5 ($PM_{2.5}$) pollution level directly and indirectly to mental stress of residents in Bangkok, Thailand. $PM_{2.5}$ induced concerns about respiratory and cardiovascular diseases, health, and unemployment served as mediators of the indirect effects. This study decomposed full perception into correct perception (actual $PM_{2.5}$ level) and misperception so that the effects of perception and its components can be examined separately. The data were daily time series, beginning July 30, 2016, and ending September 30, 2023. Unobserved perception, $PM_{2.5}$ induced concerns, and mental stress were proxied by Google's relative search volume indexes. Correct perception was the actual $PM_{2.5}$, whereas misperception was the regression residual of the full perception on the actual $PM_{2.5}$. In the full sample, full perception and misperception had significant indirect effects, whereas correct perception had a significant direct effect. Respiratory disease was the main contributor to the significant indirect effect, although concern itself was not significant. For the COVID-19 subsample, full perceptions showed significant total, direct, and indirect effects. The significant indirect effect was explained by concerns regarding respiratory diseases and health. Correct perception had a significant direct effect; its indirect effect was small and nonsignificant. The results for misperceptions were similar to those for perceptions.

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1. INTRODUCTION

The most significant environmental threat to public health worldwide is air pollution. Each year, pollution causes approximately 7 million premature deaths worldwide. Particulate matter 2.5 ($PM_{2.5}$) has been identified as the most dangerous particle [1]. In terms of economic value, it was estimated, for example, in China to cost 1,388.8 and 897.7 Chinese yuan per person per year for health impacts and for depression, respectively [2]. $PM_{2.5}$ refers to tiny particles or droplets in air with a width of ≤2.5 microns. The sources of $PM_{2.5}$ pollution are industrial processes, combustion sources (e.g., electric utilities and vehicular exhausts), fugitive sources (e.g., construction and biomass burning), and natural sources (e.g., wind erosion and sea salt aerosols) [3], [4]. Different sources contribute to the different $PM_{2.5}$ components, which in turn affect the levels of toxicity and health impacts. Such components include sulfate, nitrate, ammonium, chloride, elemental and organic carbon, crustal materials, and biological materials [3], [5].

$PM_{2.5}$ has been linked to respiratory, cardiovascular, allergic, cerebrovascular, kidney, skin, and reproductive system diseases and diabetes [6]–[9]. Ultrafine $PM_{2.5}$ particles deeply penetrate the lung wall [10]. Metabolic activation, oxidative stress and damage, mutagenicity and genotoxicity, inflammation, and immune disorders are potential mechanisms underlying $PM_{2.5}$ induced physical diseases [8], [9], [11]. $PM_{2.5}$ can also cause mental diseases [12], [13]. The direct mechanism is through induction of systemic or brain-based oxidative stress and inflammation [14] as well as dysfunctional breathing and heart performance [15], [16]. Regarding indirect mechanisms, certain $PM_{2.5}$ induced diseases, such as respiratory or cardiovascular diseases, lower work efficiency, and labor productivity [17], result in work stress, fear of unemployment, and poor mental health [18]. Mental stress increases if the $PM_{2.5}$ level exceeds the human-adaptive capability [19], whereas studies [20], [21] have also reported mental stress from concerns or fears of $PM_{2.5}$ induced diseases.

Mental health is one of the leading global health issues for 2023 [22]. Among the mental disorders, the prevalence of psychological distress at 50.0%, is followed by mental stress at 36.5% [23]. While the relationship between $PM_{2.5}$ and mental health has been investigated extensively, few studies have investigated the relationship between $PM_{2.5}$ and mental stress [24], [25]. Studies [20], [21] and [26] in China and the U.S., respectively, reported that mental stress has a significant relationship with $PM_{2.5}$ level. A study on pregnant women in Korea [27] found similar results. Previous studies have consistently reported for Bangkok residents that $PM_{2.5}$ was associated with respiratory diseases [28]–[30]; a negative correlation of $PM_{2.5}$ with daily confirmed COVID-19 cases, was found during the COVID-19 pandemic period [31]. Finally, another study [29] linked cardiovascular diseases to pollution. Studies relating $PM_{2.5}$ with mental diseases or physical diseases other than respiratory and cardiovascular diseases have not been conducted based on the Bangkok sample.

The effects of $PM_{2.5}$ on mental stress can result from perceived [20], [21] or actual $PM_{2.5}$ levels [26], [27]. It is important to note that the perception of $PM_{2.5}$ levels can be decomposed into correct perception (or actual $PM_{2.5}$ levels) and misperception. The objective of this study is to decompose this perception and use the results to examine the mechanism by which the perception and its components affect mental stress. The findings can be applied towards public health recommendations and risk communication [20]. The role of misperception in mental stress is a novel focus of this study. Misperception is measured using the regression residual of the perceived $PM_{2.5}$ level on actual $PM_{2.5}$ levels. The unobserved perception is proxied by the Google relative search volume index, which is both easy and inexpensive to collect. Endogeneity problems in the analyses, which can lead to biased and inconsistent estimates, are addressed using instrumental-variable regressions.

2. METHOD

2.1. Model

This study investigated the relationship between the perception of $PM_{2.5}$ level and mental stress using multivariate mediation analysis [32], [33]. This relationship was both direct and indirect. Regarding the indirect relationship, concern about $PM_{2.5}$ induced diseases and unwanted experiences 1 to N served as mediators. A path diagram of the analysis is shown in Figure 1.

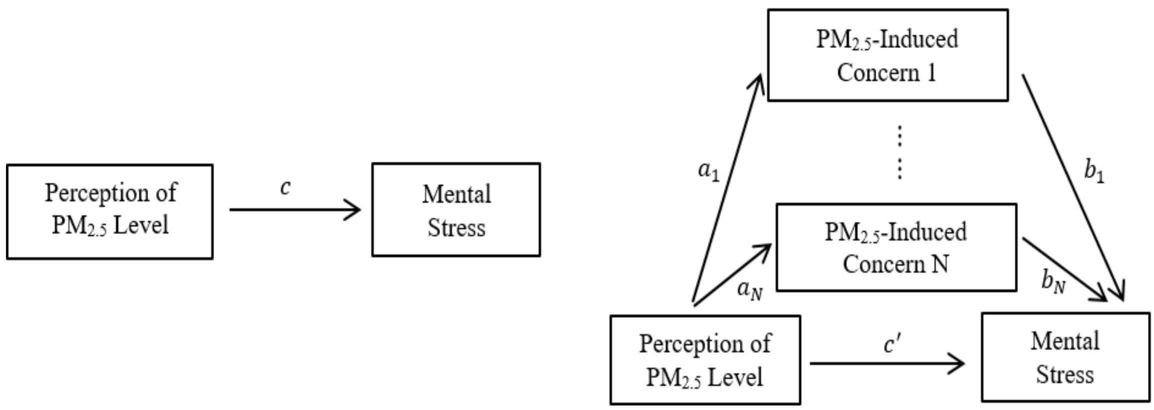

Figure 1. Path diagram of multivariate mediation analysis

Perception was the determining variable shown in Figure 1, left panel, whereas mental stress was the outcome. The aggregate relationship between the two variables is measured by the coefficient c. The direct relationship between the perception and mental stress is inferred from the coefficient c' in the right panel. This was estimated by controlling for the mediation variables. The coefficients a_1 to a_N indicate the relationship between perception and $PM_{2.5}$-induced concerns about 1–N. The relationship between concerns and mental stress is represented by coefficients b_1 to b_N. Perceptions can be divided into correct and misperceptions. Thus, the perception in Figure 1 represents full, correct, or misperceptions in the analysis.

The total and direct effects were measured using the coefficients c and c', respectively. Thus, the indirect effect equals $c - c'$, whose contributors are the concerns 1 to N. The study measures the contribution of concerns 1 to N using a_1b_1 to a_Nb_N, where $a_1b_1 + \cdots + a_Nb_N = c - c'$ [33]. In this study, the concerns were limited to N=4, that is, respiratory and cardiovascular diseases, health, and unemployment. These two diseases have significant health impacts on the Bangkok sample [28]–[30]. Respiratory diseases are of great concern to Bangkok residents [34]. These two diseases were common [6], [7], [35]–[37]. The toxicity and severity of $PM_{2.5}$ depend largely on its source and chemical composition [5]. These two factors are similar in Thailand [3], [38]–[42] and China [43]. In China, a study [35] concluded that respiratory and cardiovascular diseases are the most dangerous $PM_{2.5}$ induced diseases. Health concerns represented the perceived $PM_{2.5}$ induced health risks and diseases other than respiratory and cardiovascular diseases [20]. Unemployment is a non-health risk factor. It is induced by $PM_{2.5}$ pollution and is able to increase mental stress [18]. When N is 4, the total, direct, and indirect effects are c, c', and $a_1b_1 + a_2b_2 + a_3b_3 + a_4b_4$. Concerns 1 and 2 pertain to respiratory and cardiovascular diseases, respectively. Concern 3 concerns health, whereas concern 4 concerns unemployment.

2.2. Data

This study employed time-series data. The sample consisted of residents of Bangkok, Thailand. The $PM_{2.5}$ level was daily. Bangkok's air quality index (AQI) was measured by the Pollution Control Department of Thailand's Ministry of Natural Resources and Environment. Daily Google relative search volume (RSV) indices proxy for the unobserved full perception of $PM_{2.5}$ level, concern about $PM_{2.5}$ induced diseases, and level of mental stress. RSV indices have become increasingly popular in medical and healthcare research [44], [45]. The RSV provides deep insights into individual behavior. Individuals actively relay information about their identities, thoughts, and behaviors when searching Google [46]; they search Google only for information they prefer [47]. Compared to cohort and survey data, RSV data are easy and inexpensive to collect. Because they are time-series data, short-term relationships such as daily relationships can be tested, whereas it is hardly possible to use cohort or survey data [48]. Air quality and RSV indices can be downloaded from certain websites at any time free of charge.

Thailand is an interesting country to study mental stress. A recent survey [49] reported that eight out of ten consumers had experienced mental health issues in the past six months, with mental stress accounting for the largest share (46%). Bangkok, Thailand's capital of 1,569 square kilometers in size and more than 14 million residents, was chosen as the sample city because it is one of the most $PM_{2.5}$ polluted cities. On April 15, 2023, Bangkok was among the top 10 worst cities in the world. It ranked 7th [50], whereas at the time of writing this study (October 24, 2023), its rank was 14th [51]. In Bangkok, the main outdoor sources of $PM_{2.5}$ are vehicular exhaust (43.7%), biomass burning (24.0%), sea salt aerosols (10.5%), power plants (6.48%), and industrial emissions (4.46%) [3]. The main indoor sources are cigarette smoking and charcoal stove cooking. Indoor and outdoor $PM_{2.5}$ levels are highly correlated [38]. The major chemical components of $PM_{2.5}$ are ammonium, black carbon, chromium, iron, manganese, nickel, nitrate, sulfate, and zinc [38]–[42]. A survey [52] conducted by Thailand's Department of Health revealed that 80% of respondents were concerned about the health effects of $PM_{2.5}$. In a recent survey [34] by Bangkok University, the respondents reported that they had cough and throat irritation (57.8%), sneezing, running nose, and nosebleed (51.6%), red eye and eye irritation (31.3%), allergies (29.1%), dyspnea and pneumonia (24.4%), and body rash (17.0%). They believed $PM_{2.5}$ was the cause of these symptoms.

The data began July 30, 2016, and ended September 30, 2023 (2,619 observations). Bangkok's $PM_{2.5}$ level was downloaded from the website of Air Quality Historical Data Platform. The date July 30, 2016 was chosen because it is the first day the $PM_{2.5}$ level was reported. Due to machine failure, routine maintenance, changes in the siting of monitors, and human error, some $PM_{2.5}$ observations were missing. This study imputed the missing observations using a linear interpolation method [53].

The unobserved perception of the level of $PM_{2.5}$ and concerns about diseases, health, and unemployment were specific to Bangkok. Following a study [54], the search query for the perception was "PM 2.5". Concern for respiratory and cardiovascular diseases and mental stress used the search queries "โรคทางเดินหายใจ" (*Rokh thāng dein h̄āycı*, meaning respiratory diseases) [55], "โรคหลอดเลือดหัวใจ" (*Rokh h̄lxdleụ̄xd h̄ạwcı*, meaning cardiovascular diseases) [56], and "เครียด" (*Kherīyd*, meaning stress) [57] in the Thai language, respectively. The query for the health concern was "สุขภาพ" (*S̄uk̄hp̣hāph*, meaning health) [58], whereas that for the unemployment was "ตกงาน" (*Tkngān*, meaning unemployed) [59]. The indices were downloaded from the Google Trends.

The average and standard deviation of the $PM_{2.5}$ level were 81.693 and 1.195 AQI points, respectively. The RSV indices were relative. After scaling for the full sample, the maximum levels for the $PM_{2.5}$ perception, concerns for respiratory and cardiovascular diseases, health, and unemployment, and mental stress were 83.000, 1.800, 1.200, 100.000, 8.000, and 15.000 points, respectively, whereas the corresponding averages (standard deviations) were 1.643 (4.786), 0.061 (0.155), 0.056 (0.118), 54.163 (12.414), 0.950 (0.971), and 4.593 (1.730) points.

The $PM_{2.5}$ level, and RSV indices exhibit trends and seasonal patterns [44], [60]. For this reason, all variables were de-trended and de-seasonalized by the logged time trend and day-of-week and month-of-year dummy variables. In the final step, the variables were standardized by their averages and standard deviations so that the sizes of the coefficients and effects could be compared.

Correct perception and misperception need be measured. In this study, the correct perception was the actual $PM_{2.5}$ level. The misperception variable was the standardized regression residual of the "PM 2.5" RSV variable on the actual $PM_{2.5}$ variable. All the resulting variables were stationary but non-normal, with a zero average and unit standard deviation. This study approved by the Human Research Ethics Committee of Thammasat University (Certificate of Approval No. 009/2566).

2.3. Statistical analysis

This study conducted three linear regressions for the multivariate mediation analysis. The first regression ran the perception variable on the mental stress variable to estimate the coefficient c to measure the total effect. The second regression considered the perception variables with the concern variables for respiratory and cardiovascular diseases, health, and unemployment to test for the relationship a_1 to a_4. The third regression regressed the mental stress variable on the perception variable and the four concern variables. The coefficients b_1 to b_4 from this regression indicate the effects of the concern variables, also serving as the regression's control variables, on mental stress. The coefficient c' measured the direct effect of stress perception after controlling for concerns.rtc

It is likely that the three regressions suffer from endogeneity problems owing to omitted variables and errors in the variables [61]. This study is aware that other variables, such as health status and access to health care, could help to explain mental stress. But they are excluded from the analysis. An incomplete set of explanatory variables constitutes the omitted-variable problem. Moreover, perception, concerns, and mental stress cannot be observed. In analysis, these variables are proxied by Googlge RSVs. Alternative proxies, e.g. media coverage [62] and tweets [63], are possible; these proxies may encompass information on individual experiences and awareness the RSVs cannot capture. The fact that RSVs are proxies and cannot capture all the relevant information implies that the RSVs have measurement errors, thus leading to the errors-in-vatables problem.

To mitigate these problems, this study used a generalized method of moments (GMM) regression [64]. The GMM is an instrumental variable (IV) regression technique that returns consistent, asymptotically normal, and efficient estimates even for non-normal variable specifications. The IVs were constructed using a two-step technique [65]. Pal's IVs [66] were inputs in the first step. Statistical tests were performed based on the heteroscedasticity and autocorrelation-consistent standard deviation [67]. The standard deviations for the individual and aggregate indirect effects were computed using this method [33]. All estimations and tests were processed using the statistical program EViews version 9.5 (IHS Global, Inc.).

3. RESULTS

This study estimated the coefficients of the multivariate mediation model in Figure 1 and used them to compute the direct and indirect effects of full perception, correct perception (actual $PM_{2.5}$ level), and misperception on mental stress. The indirect effect is the sum of the four components resulting from concerns about respiratory and cardiovascular diseases, health, and unemployment. In this study, significance corresponds with a p-value of 0.05 or lower. (The coefficient estimates are not shown. These data are available from the corresponding author upon request.).

3.1. Full sample

Table 1 presents the results for the entire sample. Column 2 shows that the total effect of full perception was not significant. The direct effect was negative but not significant, whereas the indirect effect was positive and significant. The indirect effect was significantly larger than the direct effect. The total effect was the sum of the direct and indirect effects. Thus, it is likely that the nonsignificance results from the fact that the direct and indirect effects cancel each other. The sum of the effects of the four concerns was a significant indirect effect. Respiratory diseases contributed to 47.83% of the indirect effects. Although not significant, its p-value was low (0.091).

This study decomposed full perception into correct perception (actual $PM_{2.5}$ level) and misperception components. The shares of these two components were 2.27% and 97.73%, respectively. Despite its much smaller share, correct perception has a greater influence on mental stress than misperception. From the regression analysis, the R^2 coefficient of correct perception was 0.009, compared with the 0.001 R^2 coefficient of misperception.

Table 1. Effects of perception of $PM_{2.5}$ level on mental stress for the full sample (July 30, 2016 to September 30, 2023)

Effect	Full perception	Components of perception	
		Actual $PM_{2.5}$ level, correct perception	Misperception
Total effect (c)	0.019	0.099	-0.007
Direct effect (c')	-0.005	0.090*	-0.028
Indirect effect $(c - c' = a_1b_1 + a_2b_2 + a_2b_2 + a_2b_2)$	0.024*	0.010	0.021*
(1) Respiratory diseases (a_1b_1)	0.011	0.010*	0.009
(2) Cardiovascular diseases (a_2b_2)	0.002	0.001	0.002
(3) Health (a_3b_3)	0.005	-0.002	0.005
(4) Unemployment (a_4b_4)	0.005	0.001	0.005

*$p \leq 0.05$.

Column 3 of Table 1 reports the effects of the correct perception. The direct effect is statistically significant. It is eight times larger than the indirect effect. Concern about respiratory diseases was the largest contributor to the indirect effect, and it was significant. However, summing this with the remaining three concerns constitutes the indirect effect, which was not significant. Column 4 of Table 1 reports the results for misperception. As misperception explains most perceptions, their effects on mental stress are very similar.

3.2. COVID-19 subsample

COVID-19 has caused a global pandemic. To contain spread of the disease, quarantines have been imposed in almost all capitals and major cities worldwide, resulting in a significant improvement in air quality. The average reduction in $PM_{2.5}$ pollution was 12% [68]. When $PM_{2.5}$ pollution fell, mental stress rose [69]. Thailand and its capital Bangkok experienced the same situations [70], [71]. This study examined the effects of the COVID-19 period to gain insights into the contribution of falling $PM_{2.5}$ level and rising mental stress. The COVID-19 subsample began on April 3, 2020, and ended on September 30, 2022) [72]. The results are summarized in Table 2.

Table 2. Effects of perception of $PM_{2.5}$ level on mental stress for the COVID-19 subsample (April 3, 2020 to September 30, 2022)

Effect	Full perception	Components of perception	
		Actual $PM_{2.5}$ level, correct perception	Misperception
Total effect (c)	0.228*	0.121*	0.159*
Direct effect (c')	0.157*	0.104*	0.090
Indirect effect $(c - c' = a_1b_1 + a_2b_2 + a_2b_2 + a_2b_2)$	0.071*	0.017	0.069*
(1) Respiratory diseases (a_1b_1)	0.019*	0.001	0.018*
(2) Cardiovascular diseases (a_2b_2)	0.000	0.000	0.000
(3) Health (a_3b_3)	0.035*	0.007	0.037*
(4) Unemployment (a_4b_4)	0.017	0.009	0.013

*$p \leq 0.05$.

Column 2 of Table 2 shows that the total, direct, and indirect effects of the full perceptions are significant. For the indirect effect, the significant components were concerns about respiratory diseases and health. Health concerns were almost two times that of respiratory diseases. In the COVID-19 subsample, full perception was composed of 11.91% correct perception, whereas misperception had an 88.09% share. The explanatory abilities of the two components were approximately the same. Their R^2 coefficients of the regressions for mental stress were 0.012 and 0.010, respectively. Column 3 of Table 2 reports the effects of correct perception. The total and direct effects are statistically significant. The indirect effect and its four components were not statistically significant. Finally, column 4 of Table 2 shows that the total effect of misperception is significant. The significant result was from the indirect effect, whose significant components were concerns about respiratory diseases and health. This result was similar to that of the full perceptions.

4. DISCUSSION

The perceived and actual levels of $PM_{2.5}$ affect mental stress [20], [27]. Previous studies [20] based on perceived $PM_{2.5}$ levels did not distinguish whether the relationship was from the actual level (correct perception) or misperception. One study Chen *et al.* [73] acknowledged that decomposition is difficult; therefore, the sources of the effects could not be identified. This study was able to unbundle the perceived level into the actual level and misperceptions.

This study decomposes full perception into correct perception (actual $PM_{2.5}$ level) and misperception components, so that the effects of perception, actual $PM_{2.5}$ level, and misperception can be measured and tested separately. Concerns about health risks in previous studies [20], [21], which served as mediators, were general. In this study, concerns about specific $PM_{2.5}$ induced diseases were considered, together with health risks. Unemployment was included as a mediation variable. Concern about unemployment due to $PM_{2.5}$ pollution is possible [18].

Most epidemiological studies on the relationship between $PM_{2.5}$ and mental health have chosen cohort or survey data [24], [25]. Obtaining a sufficient number of participants and covering a long observation period for a cohort or survey study is costly and time-consuming [48]. Although individual-level data are accurate and preferred, benefits relate to the ways in which the data are included in the analyses [74]. Moreover, questionnaire responses tend to suffer from unreliability and measurement errors [75].

In this study, tests were conducted based on daily observations. The finding that these effects are significant indicates that they materialize on the day of exposure to pollution. The immediate effects found in this study are consistent with those in a Paris study [76], in which $PM_{2.5}$ effects on mental stress were immediate and short-term, within one day. This contradicts the results of the Nanjing study [20], which found no evidence to support the direct effect of real-time $PM_{2.5}$ exposure. The different conclusions of this study and the Paris study [76] from the Nanjing study [20] regarding the immediacy of the effects can be explained by the sample used. While the former used daily time-series data, the latter used survey data.

For the full sample and COVID-19 subsample, the significant effect for perception is consistent with other studies [20], whereas the significant effects for correct perception (actual $PM_{2.5}$ level) is also supported by a previous report [27]. In this study, the significant results for the correct perception (actual $PM_{2.5}$ level) are explained by the direct effect. This finding supports the fact that $PM_{2.5}$ toxicity, and human responses link actual $PM_{2.5}$ level directly with metal stress [14]–[16]. However, this does not support the findings of the study by Liu *et al.* [20], which did not find any direct effect. Liu *et al.* [20] argued that the mental stress was "subjected to the indirect influence of physical symptoms, by increasing perceived effect on health and increasing attribution to indoor pollution sources."

There was a significant indirect effect of misperception on mental stress. Its direct effect is non-significant. This study found that misperception accounted for 97.73% and 88.09% of the perception of the full sample and COVID-19 subsample, respectively. Moreover, Chen *et al.* [77] reported that the respondents' perception of $PM_{2.5}$ levels depended on factors such as age, education level, family income, and history of respiratory diseases. The perception is likely to be a misperception. Misperception has no direct relationship with mental stress [14]–[16]. This indirect effect was mediated by $PM_{2.5}$ induced concerns [20].

The indirect effect was the sum of the four $PM_{2.5}$ induced concerns. In the full sample for misperception, concerns about respiratory diseases explained most of the significant indirect effects. Its share was 42.86%, whereas the remaining concerns regarding cardiovascular diseases, health, and unemployment were 9.52%, 23.81%, and 23.81%, respectively. None of these concerns were significant. Limited awareness of $PM_{2.5}$ and other pollutants, and associated diseases and health problems was also found in an early study in the United Kingdom [78].

The significance of the concerns linked to indirect effects is more pronounced for the COVID-19 subsample. Significant concerns included respiratory diseases and health. Cardiovascular diseases and unemployment were not found to be significant concerns. Despite a low $PM_{2.5}$ pollution level in the COVID-19 subsample [70], the significant $PM_{2.5}$ induced concern of respiratory diseases is supported by a study [79] that found that public interest, measured by Google RSV indexes, significantly increased during the COVID-19 period. Saeed *et al.* [80] reported that COVID-19 increased individual and public health awareness. Bangkok residents revealed their health awareness and its relationship with COVID-19 and $PM_{2.5}$ pollution in a survey [52].

The sample comprises Bangkok residents and their perception of $PM_{2.5}$. Different $PM_{2.5}$ sources in various areas contribute varying levels and types of toxic components. Thus, health impacts and risk perception vary among cities [81]. Perception is influenced by residents' exposure to environmental news and media coverage, shaping their knowledge about air pollution [82], whereas such news and coverage are highly localized [83]. Finally, perception is not solely dependent on the actual $PM_{2.5}$ level; other factors such as health infrastructure also play significant roles [84]. Therefore, the findings of this study are confined to Bangkok, Thailand, and may not be universally applicable to other cities or countries.

5. CONCLUSION

Multivariate mediation analysis was used to examine the total, direct, and indirect relationship of the perception of $PM_{2.5}$ level on mental stress for Bangkok residents. The effects on mental health are significant. A direct effect was caused by correct perception (actual $PM_{2.5}$ level). Misperception had an indirect effect, in which concerns about respiratory diseases and health were significant mediators. Although the literature points to the importance of cardiovascular diseases and possible job displacement, residents are unaware of the potential threats. After the COVID-19 outbreak ended and economic activities returned to normal, $PM_{2.5}$ pollution started to increase. Regulators must closely monitor $PM_{2.5}$ pollution levels, and strictly control emissions from the main sources. Additionally, it is important to raise public awareness that $PM_{2.5}$ induced diseases are not limited to the respiratory system. Serious diseases such as cardiovascular, cerebrovascular, and even kidney or reproductive diseases are possible. Perception varies among cities and countries, meaning that the effects of $PM_{2.5}$ on mental stress and the mediating factors involved can vary significantly. Results from different cities and countries are intriguing, suggesting the need for comparative studies in future research.

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