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Self-Assessment Adaptive Capacity Indicators of Health Risks from Air Pollution

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Abstract: This research proposes a set of 12 self-assessed air pollution adaptive capacity (APAC) indicators to determine and mitigate individual-level air pollution-related health risks. In the study, the APAC indicators were first statistically validated based on data from panels of experts using structural equation modeling. The validated indicators were subsequently transformed into a questionnaire to measure the individual-level APAC index. For ease of interpretation, the APAC index was converted into an APAC grade. The APAC grade was compared against the grading criteria based on Air Quality Index (AQI) levels to assess the individual-level health risks from air pollution. The proposed APAC-based self-assessment program to determine the individual-level health impacts from air pollution could be adopted as an economical and efficient alternative to costly and complicated clinical assessment.

Keywords: air quality index; health risk; adaptive capacity; self-assessment; air pollution

1. Introduction

Air pollution claimed an estimated seven million lives annually worldwide [1–4]. The World Health Organization (WHO) and several studies reported that people in urban areas breathe air contaminated with high levels of pollutants [5,6]. Specifically, more than 80% of urban residents are exposed to indoor and outdoor air pollution that exceeds WHO air quality guideline limits, and the situation worsens in low- and middle-income countries [7–9].

Evidence shows that exposure to air pollutants can cause respiratory disorders, ranging from cough and shortness of breath to asthma [6,10]. The long-term health risks of air pollution include severe asthma and cardiovascular diseases and death [1,3,11,12]. The elderly and small children face greater risk from air pollution than any other age group [13–15].

According to Guan, Zheng [16], Jiang, Mei [17], Rush, McDermid [18], Choi, Oh [19], Dabass, Talbott [20], the worsening air quality during the past 30 years has contributed to increased incidence of chronic illnesses. Constant exposure to air pollution, despite low concentrations, could cause anemia, allergy, eye inflammation, itchy skin rash, lung disease, and kidney failure [21]. Evidence also reported the presence of carcinogenic substances in polluted outdoor air [22].

Air pollutants, especially heavy metals, are potentially harmful to human health. Meanwhile, the current clinical assessment methods (i.e., blood test, urine test and hair follicle test) to detect elevated levels of heavy metals in the body are lengthy and expensive. Evidence shows that higher individual-level air pollution adaptive capacity helps mitigate the harmful health impacts of air pollutants and heavy metals [23–25]. Specifically, the proposed APAC-based self-assessment program identifies the APAC indicators that require attention and corrective action, as evidenced by low APAC scores. In addition, the adoption of the individual-level APAC self-assessment as a pre-clinical alternative to the clinical assessments helps reduce the lengthy waiting time and offers monetary savings to users.

The direct costs of air pollution at an individual level include the financial outlays related to the provision of medical care to the individual and the resources supporting the provision process [24,25]. Besides, there are indirect costs which are borne by the individual and society. Unlike direct costs, the indirect costs are more difficult to quantify. Examples of the indirect costs of air pollution-induced illnesses are loss of enjoyment of goods, physical and psychological discomfort, and a reduced quality of life [23–25].

Specifically, this research proposes a set of indicators of adaptive capacity to air pollution to assess and mitigate the individual-level health risks related to air pollution. The individual-level air pollution-related health risks are measured by an air pollution adaptive capacity (APAC) index, which is converted into an APAC grade for ease of interpretation. In the study, the APAC indicators were first statistically validated based on data from panels of experts in medicine, health care, and environment. The expert-validated APAC indicators were then transformed into a 12-question questionnaire to measure the individual-level APAC index and converted into an APAC grade. To assess the health risks of an individual from air pollution, the APAC grade is compared against the grading criteria which are based on 7-day average U.S. Air Quality Index (AQI) levels.

Essentially, the proposed APAC-based self-assessment program to determine the individual-level health impacts from air pollution could be adopted by the general public as an alternative to clinical assessment which is costly and requires specialist expertise [26,27].

2. Literature Review

Air pollution is more common in densely populated urban areas. Urbanization affects the atmospheric diffusion capability of the area and the levels of airborne pollutants [28]. Specifically, urbanization increases the phenomenon of haze weather, which in turn decreases urban wind speed and reduces pollutant diffusion capability, resulting in accumulation of airborne pollutants [29–31].

Nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and carbon monoxide (CO) are pre-dominant pollutants in outdoor air pollution. Exposure to high-intensity NO₂ in very confined spaces likely results in death, while exposure to ambient NO₂ increases the risk of respiratory tract infections. SO₂ could induce respiratory disorders in healthy individuals and those with underlying pulmonary diseases [8,32,33]. Exposure to moderate and high levels of CO over long periods of time is closely linked to increased risk of heart disease, while exposure to excessive CO levels can result in unconsciousness or even death.

Excessive air pollutants can cause respiratory disorders, especially in those who are required to stay outdoors or engage in outdoor activities. Exposure to excessive air pollutants also triggers cardiovascular conditions, such as high blood pressure and accelerated atherosclerosis. Outdoor activities should be avoided to reduce health effects from exposure to excessive air pollutants [34–38]. In addition, taking a shower and changing into new clothes after outdoor activities is effective in removing dirt and pollutants on the skin [39,40]. Tiwari [41], Ravindra, Wauters [42], Goel, Gani [43] found that pedestrians were at higher risk of exposure to air pollutants than passengers on a bus or in a car.

Jarjour, Jerrett [44]; Mohan [45] argued that the benefits of outdoor activities for healthy individuals, such as cycling and running, far outweigh the risk of exposure to outdoor air pollution. Regular exercise reduces oxidative stress [46–49]. Nevertheless, cyclists and

runners should select routes with low vehicular traffic to reduce unnecessary exposure to airborne pollutants.

For those working outdoors in heavily polluted environments, an ultrafine dust-proof mask (3 microns or less pore size) or NIOSH-certified N95 respirator is strongly recommended to effectively protect against harmful air pollutants [36,50–54].

According to [55,56], air pollutants intensify the ultraviolet (UV) radiation from sunlight. In other words, the dirtier the air, the more intense the UV radiation reaching the Earth's surface as the air pollutants diffuse and refract the sunlight and UV radiation. Specifically, the diffusion and refraction caused by the air pollutants increase the intensity of UV radiation.

In addition to air pollution, ultraviolet (UV) from the sun can cause skin cancer [17,57–60]. A simple and effective preventative measure is to limit skin exposure to UV rays to preserve the integrity of the epidermis [61,62]. When in the sun, it is advisable to apply sunscreen products with PA+++ and SPF30 to protect the skin against UVA and UVB and to reduce UV-induced skin disorders [63–66].

Table 1 tabulates the air pollution adaptive capacity (APAC) indicators from a review of the existing literature. There are 12 APAC indicators that are related to practices and/or behavior that could mitigate the health risks of air pollution on individual persons.

Table 1. Summary of the APAC indicators relating to practices to mitigate the individual-level health impacts of air pollution.

Indicator ID	Description	References
A1	Avoid leaving place of residence without proper protection when AQI levels are too high (AQI > 101).	[34–37]
A2	Wear an N95 mask or equivalent when engaging in outdoor activity and AQI levels are too high (AQI > 101).	[36,50–54]
A3	Apply sunscreen products with PA+++ and SPF30 to protect against UVA and UVB.	[63–66]
A4	Adopt diet regimens that lower oxidative stress.	[59,67–78]
A5	Install indoor air filter systems certified by one of the following institutes: the British Allergy Foundation (BAF), the Association of Home Appliance Manufacturers (AHAM), and the European Centre for Allergy Research Foundation (ECARF).	https://www.allergyuk.org/ (accessed on 1 September 2021) https://www.ecarf.org/en/ (accessed on 1 September 2021) https://www.aham.org/ (accessed on 1 September 2021)
A6	Exercise regularly to reduce oxidative stress.	[46–49]
A7	Take a shower and change into new clothes upon returning to place of residence (following outdoor activity).	[39,40]
A8	Take dietary supplements to reduce oxidative stress.	[59,67–78]
A9	Avoid outdoor exercise and/or activities when AQI levels are too high (AQI > 101).	[7,32,79–83]
A10	Stay hydrated by drinking clean water every 2–3 hours, and the recommended quantity is 1.5 liters/day (8–10 glasses) for adult.	[84–87]
A11	Elderly individuals with preexisting health conditions should avoid exposure to air pollution.	[80,81,88,89]
A12	Aware of the health impacts of air pollution and equip oneself with relevant knowledge to mitigate the impacts.	[90–93]

Air Quality Index (AQI) indicates the levels of pollutants in the air and the associated health risks to individuals exposed to the pollutants. The AQI is based on hourly, daily, or weekly measured levels of particulate matter (PM), nitrogen dioxide, carbon monoxide, sulfur dioxide, and atmospheric ozone. Table 2 tabulates the air quality index levels of

health concern and corresponding U.S. AQI numerical values (<https://www.epa.gov/> (accessed on 1 September 2021)).

Table 2. AQI levels, numerical values and explanations.

Air Quality Index Levels of Health Concern	Numerical Value	Explanation and Recommendations
Good	0–50	Air quality poses minimal or no serious health risk.
Moderate	51–100	Air quality is somewhat satisfactory. Sensitive individuals nevertheless should avoid outdoor activity due to possible respiratory symptoms.
Unhealthy for sensitive groups	101–150	Sensitive individuals are susceptible to irritations and respiratory disorders.
Unhealthy	151–200	Increased likelihood of effects on the heart and lungs among general public, and the health impacts are more severe in sensitive groups.
Very unhealthy	201–300	Sensitive individuals are likely to experience frequent fatigue. Sensitive individuals are advised to remain indoors and restrict activities.
Hazardous	301–500	Sensitive individuals are at high risk of serious health effects. Everyone is strongly advised to avoid exercise and remain indoors.

3. Research Methodology

This research assesses the individual-level health risks from air pollution based on 12 APAC indicators (Table 1). The individual-level health risks linked to air pollution are measured by individual-level APAC index values that are converted into APAC grades for ease of interpretation. To assess the levels of health risks of individuals from air pollution, the APAC grades are compared against the grading criteria which are based on 7-day average U.S. AQI levels (Table 3).

Table 3. Individual-level APAC index and grading in relation to the AQI levels of air pollution.

Individual-Level APAC Index	Individual-Level APAC Grade	Meaning
81–100	A+	Excellent self-protection against air pollution, with minimal to no health risks given that the AQI levels are below 500 *.
71–80	A	Very good self-protection against air pollution, with minimal to no health risks given that the AQI levels are below 300.
61–70	B	Good self-protection against air pollution, with minimal to no health risks given that the AQI levels are below 200.
51–60	C	Adequate self-protection against air pollution, with minimal to no health risks given that the AQI levels are below 150.
41–50	D	Limited self-protection against air pollution, with minimal to no health risks given that the AQI levels are below 100.
0–40	F	No self-protection against air pollution.

Note: * Refer to Table 3 for explanations on the AQI levels.

A review of existing research and publicly available information is first undertaken, including publications on air pollution, air pollution-related health impacts, preventive action against ambient (indoor and outdoor) air pollutants, and individual-level adaptive responses to air pollution. The indicators that are closely related to individual-level air pollution adaptability are identified and selected, and there are 12 APAC indicators (Table 1).

The relevance of 12 APAC indicators is statistically validated using structural equation modeling (SEM) based on data collected from panels of experts. The expert-validated APAC indicators are transformed into questionnaires to determine the individual-level APAC index. For ease of interpretation, the individual-level APAC index is converted into an APAC grade. To assess the individual-level health risks from air pollution, the APAC grade is compared against the grading criteria which are based on 7-day average U.S. AQI

levels. This research focuses on measurements of five air pollutants in assessment of air pollution-induced health risks of individual persons, including particulate matter (PM_{2.5} and PM₁₀), nitrogen dioxide (NO₂), carbon monoxide (CO), sulfur dioxide (SO₂), and ozone (O₃).

3.1. Validation of the APAC Indicators

To validate the APAC indicators, the adaptive capacity indicators were transformed into a 12-question self-assessment questionnaire (Questionnaire I) and validated by panels of experts (215 participants), including medical doctors (55), nurses (8), medical technicians (45), pharmacists (28), anti-aging scientists (68), and environmental scientists (61). Questionnaire I is provided with the number of questions (12 questions) corresponded to the APAC indicators (12 indicators).

In the data collection, the 12-question questionnaire was initially sent electronically to a randomly selected group of 500 experts, and there were 215 respondents. According to Dawson, Peppe, and Wang (2011), a proper sample size is no less than 10 times the number of questions. In addition, a sample size of 200 samples is the minimum requirement for structural equation modeling (Hair, Sarstedt, Ringle, and Mena, 2012; Anderson and Gerbing, 1984; Bollen, 1989).

In Questionnaire I, an 11-point Likert scale was used where 0 represents strongly disagree and 10 strongly agree that a given APAC indicator is related to the individual-level health risks from air pollution. According to Bayraktar, Tatoglu [94]; Ismail Salaheldin [95]; Thanvisitthpon, Shrestha [96], a measure scale could be used with self-assessment questions.

Prior to SEM analysis, the Kolmogorov-Smirnov test was applied to the data collected from 215 experts using Questionnaire I, with the null hypothesis (H₀) being that the data are normally distributed [97]. The coefficient of the Kolmogorov-Smirnov test was 0.557. Given that H₀ is accepted if the observed statistic is greater than the critical value ($\alpha > 0.05$), H₀ was thus accepted, indicating that the data are normally distributed [98–101].

In the SEM analysis, exploratory factor analysis (EFA) was first carried out, followed by confirmatory factor analysis (CFA). In the EFA, the 12 APAC indicators were validated based on the experts' responses and then statistically classified into groups by APAC components. There were three EFA-classified APAC components: Components I, II, and III, as presented in Table 4.

Table 4. Exploratory factor analysis of 12 APAC indicators and component-based factor weight scores.

Indicator ID	Indicator-Level Factor Loading (α_i)	Component-Based Factor Weight Scores		
		Component I	Component II	Component III
A8	0.797	0.779		
A4	0.737	0.773		
A10	0.641	0.721		
A5	0.514	0.535		
A3	0.544	0.522		
A9	0.341		0.784	
A11	0.673		0.728	
A12	0.697		0.509	
A7	0.389			0.763
A1	0.489			0.639
A6	0.676			0.527
A2	0.409			0.428
Total Initial Eigenvalues		3.834	1.378	1.107
% of Variance		31.953	11.484	9.229

The APAC indicators and components were further validated by CFA to determine the factor loadings and reliability of the indicators and components. The reliability of APAC

indicators and components are measured by indicator-level reliability (R^2) and composite reliability (CR) (Table 5). The factor loading (between 0–1) indicates the degree of relevance of an APAC component or indicator of individual-level adaptive capacity to air pollution.

Table 5. Confirmatory factor analysis of APAC components and indicators.

Component	APAC Indicators	Indicator-Level Reliability (R^2) *	Validity of APAC Components	
			Composite Reliability (CR) **	Average variance Extracted (AVE)
Component I				
(Component-level factor loading = 0.974)	A8	0.636	0.949	0.786
	A4	0.544		
	A10	0.410		
	A5	0.364		
	A3	0.396		
Component II				
(Component-level factor loading = 0.631)	A9	0.316	0.408	0.601
	A11	0.453		
	A12	0.486		
Component III				
(Component-level factor loading = 0.806)	A7	0.352	0.650	0.563
	A1	0.339		
	A6	0.456		
	A2	0.367		

* R^2 indicates the reliability of APAC indicator, given that $R^2 > 0.3$ is statistically acceptable. ** CR indicates the reliability of APAC component, given that CR > 0.6 or AVE > 0.5 is statistically acceptable.

3.2. Individual-Level APAC Index

After SEM validation, a second set of 12-question APAC questionnaire (Questionnaire II) was developed and applied to assess the individual-level health risks related to air pollution. The questionnaire asks respondents for information about habitual behavior or actions to mitigate the air pollution-induced health impacts. Questionnaire II is provided in Supplementary Materials, and the number of questions (12 questions) corresponded to the SEM-validated APAC indicators (12 indicators).

In the data collection for Questionnaire II, a six-point Likert scale was used to obtain APAC indicator scores, where 0 indicates no action to mitigate the health impacts of air pollution and 5 indicates that the respondent takes every possible action to mitigate the impacts.

The APAC indicator scores (i.e., 0, 1, 2, 3, 4, or 5) were converted into weighted average scores (WAC; Equation (1)), and the factor loadings of 12 APAC indicators were normalized by using Equation (2) for normalized factor loadings. The normalized factor loadings were multiplied by WAC for normalized indicator-level adaptive capacity scores and then summed to obtain the individual-level APAC index (from 0–1; Equation (3)). The APAC index was multiplied by 100 and a grade given. The grades correspond to the U.S. AQI levels.

The weighted average score (WAC; 0.0, 0.2, 0.4, 0.6, 0.8, 1.0) of each of 12 APAC indicators is mathematically expressed as

$$WAC = \frac{\text{APAC indicator score}}{5} \quad (1)$$

where the APAC indicator score ranges from 0–5, corresponding to the six-point Likert scale; and 5 (the denominator) is the constant representing the maximum score for each APAC indicator.

The normalized indicator-level factor loading of each of 12 APAC indicators is calculated by Equation (2), where y_i is the normalized factor loading of each APAC indicator, x_i

is the EFA-validated factor loading of each of the APAC indicators ($i = 1, 2, \dots, 12$), and Z is the summation of the factor loadings of 12 APAC indicators.

$$y_i = x_i / Z \quad (2)$$

The individual-level APAC index is the summation of the product of normalized factor loadings (y_i) and WAC of 12 APAC indicators, which is multiplied by 100.

$$\text{Individual-level APAC index} = \sum_{i=1}^{12} (y_i \cdot \text{WAC}_i) \times 100 \quad (3)$$

For ease of interpretation, a grade is assigned to the individual-level APAC index (i.e., A+, A, B, C, D, and F), in relation to the U.S. AQI levels of air pollution (Table 3).

4. Results and Discussion

4.1. Exploratory Factor Analysis of APAC Indicators

Table 4 tabulates the EFA-validated APAC indicators and corresponding indicator-level factor loadings (x_i). The EFA statistically classified the 12 APAC indicators into three APAC components with corresponding component-based factor weight scores: Components I, II, and III.

Component I consisted of five APAC indicators: A3, A4, A5, A8, and A10 with the component-based factor weight scores of 0.522–0.779. Component II consisted of three APAC indicators: A9, A11, and A12 with the component-based factor weight scores of 0.509–0.784, and Component III contained four indicators: A1, A2, A6, and A7 (0.428–0.763).

In Table 4, the component-based factor weight scores of all 12 APAC indicators (0.428–0.784) were greater than 0.3, indicating that the APAC indicators were assigned to appropriate APAC components given that a factor weight score > 0.3 is statistically acceptable [102–105]. The eigenvalues of Components I, II, and III were 3.834, 1.378, and 1.107, respectively, given that an eigenvalue > 1.0 is statistically acceptable, with the corresponding percentage of variance of 31.953, 11.484, and 9.229.

The factor loadings of the APAC components were 0.631–0.974 and those of 12 APAC indicators were 0.341–0.797 (Figure 1), given a factor loading greater than 0.3 is statistically acceptable (Kim and Mueller [106]). Besides, the chi-square = 617.172, degree of freedom (df) = 66, p -value = 0.000, adjusted goodness of fit index (AGFI) = 0.926, goodness of fit index (GFI) = 0.958, NFI Delta1 = 0.905, confirmatory fit index (CFI) = 0.971, root mean square error of approximation (RMSEA) = 0.041, incremental fit index (IFI) = 0.973, and Tucker–Lewis index (TLI) = 0.957. According to Baumgartner and Homburg [107], Gatignon [108] and Hooper, Coughlan [109], AGFI, GFI, NFI Delta1, CFI, IFI, and TLI should be close to 1, while RMSEA should not exceed 0.05.

4.2. Confirmatory Factor Analysis of EFA-Validated Components and Indicators

Table 5 presents the CFA results of three APAC components and 12 APAC indicators. The indicator-level reliability (R^2) of the APAC indicators under Components I, II, and III were 0.364–0.636, 0.316–0.486, and 0.339–0.456, given that $R^2 > 0.3$ is statistically acceptable. The composite reliability (CR) of Components I, II, and III were 0.949, 0.408, and 0.650, and the corresponding average variance extracted (AVE) were 0.786, 0.601, and 0.563. According to Fornell and Larcker [110], a CFA-validated component is statistically valid if $\text{CR} > 0.6$ or $\text{AVE} > 0.5$.

In this research, a high indicator-level factor loading indicates that the APAC indicator plays a significant role in lowering individual-level health risks related to air pollution. As shown in Figure 1, the indicator A8 (take dietary supplements to reduce oxidative stress) under Component I had the highest indicator-level factor loading (0.797) and A4 (adopt diet regimens that lower oxidative stress) had the second-highest indicator-level factor loading (0.737). The findings indicated that A8 and A4 play a significant role in cutting down the individual-level health risks related to air pollution. Despite the lowest

indicator-level factor loading (0.389), A7 (take a shower and change into new clothes upon returning to place of residence) under Component II is the practice that requires minimal efforts to mitigate the individual-level health impacts caused by air pollution.

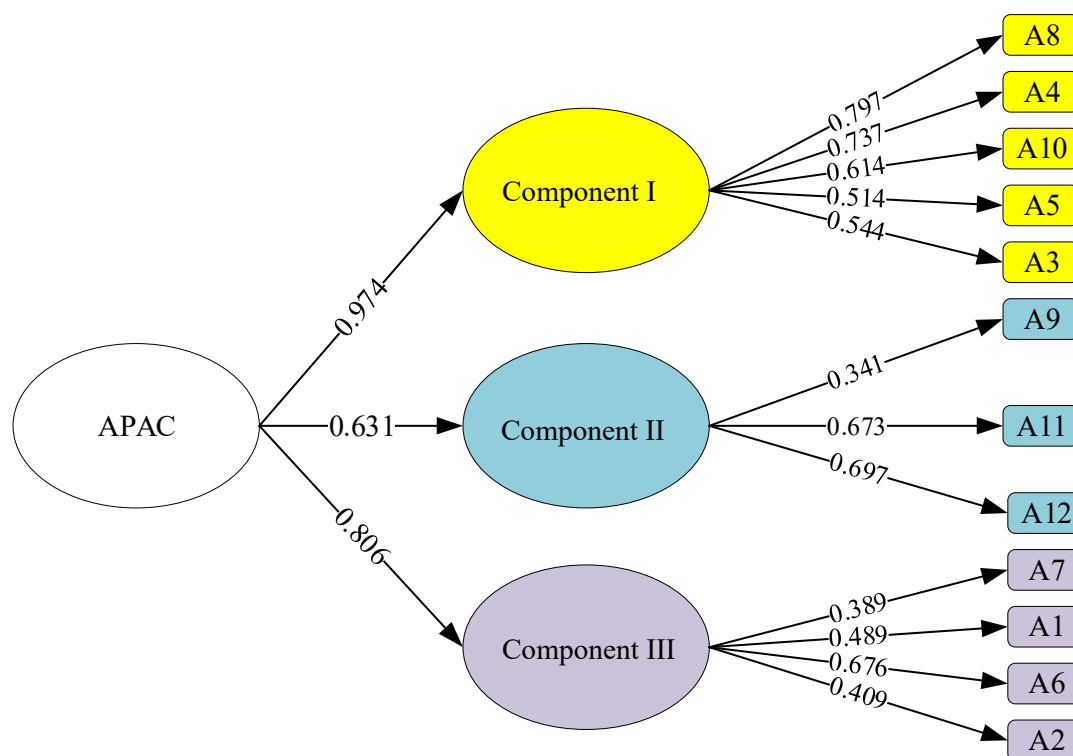


Figure 1. Factor loadings of the EFA-validated APAC components and 12 APAC indicators.

Regular intake of dietary food and supplements reduces air pollution-related oxidative stress, corresponding to the SEM findings in which the highest and second-highest factor loadings belong to the APAC indicators A8 (0.797) and A4 (0.737) [59,67–78]. According to Whyand, Hurst [68], Péter, Holguin [67], Zhang [69], Künzli, Jerrett [74], proper types and doses of vitamins, minerals, and nutrients lower the individual-level health impacts related to air pollution, including respiratory tract allergy, pneumonia, respiratory tract disease, lung cancer, and cardiovascular disease.

4.3. Calculation of APAC Index

This section shows the calculation of the individual-level APAC indexes of three subjects (Individuals I, II, III) based on the weighted average score (Equation (1)), normalized indicator-level factor loading (Equation (2)), and individual-level APAC index (Equation (3)). The 7-day average AQI level was identical (AQI = 143; Unhealthy for sensitive groups), but the adaptive capacities to air pollution of the three subjects were unequal. Table 6 presents the individual-level APAC index calculations and results for Individuals I, II, III and the corresponding APAC grades. There are five APAC grades: A+, A, B, C, D, and F (Table 3).

Given the 7-day average AQI level of 143 (Unhealthy for sensitive groups), the passing APAC grade is thus a C. In Table 6, the APAC grade of Individual I is C, indicating adequate self-protection against air pollution (Table 3). The WAC of indicators A1, A4, and A6 for Individual I are very low (0.2). To improve the APAC grade and reduce the individual-level air pollution-induced health risks, Individual I should alter behavior and activities relating to the indicators A1 (avoid leaving place of residence without proper protection when AQI levels are too high (AQI > 101)), A4 (adopt diet regimens that lower oxidative stress), and

A6 (exercise regularly to reduce oxidative stress). The emphasis should be placed on A4, given very high indicator-level factor loading (0.737).

Table 6. Individual-level APAC index of Individuals I, II, and III.

APAC Component	APAC Indicator	Indicator-Level Factor Loading	Normalized Indicator-Level Factor Loading (Equation (2))	Weighted Average Score Based on Questionnaire II (Equation (1))		
				Individual I	Individual II	Individual III
Component I	A8	0.797	0.116	0.8	0.2	0.8
	A4	0.737	0.107	0.2	0.2	0.6
	A10	0.614	0.089	0.8	0.4	0.8
	A5	0.514	0.075	0.6	0.2	1.0
	A3	0.544	0.079	0.6	0.4	0.6
Component II	A9	0.341	0.050	0.4	0.4	0.6
	A11	0.673	0.098	0.8	0.2	0.8
	A12	0.697	0.101	0.6	0.2	1.0
Component III	A7	0.389	0.057	0.4	0.4	0.8
	A1	0.489	0.071	0.2	0.2	0.8
	A6	0.676	0.098	0.2	0.4	0.8
	A2	0.409	0.059	0.4	0.4	0.6
Individual-level APAC index (Equation (3))				51.7	28.6	77.6
Individual-level APAC grade				C	D	B

The APAC grade of Individual II is D, indicating limited self-protection against air pollution (Table 3). The WAC of indicators A1, A4, A5, A8, A11, and A12 of Individual II are very low (0.2). As a result, Individual II is required to alter behavior and activities relating to these APAC indicators in order to improve the APAC grade. On the other hand, Individual III receives a high APAC grade of B, indicating good self-protection against air pollution. To further improve the APAC grade, Individual III could adopt new behaviors and actions relating to the indicators A5 (install indoor air filter systems certified) and A12 (aware of the health impacts of air pollution and equip oneself with relevant knowledge to mitigate the impacts).

5. Conclusions and Recommendations

This study proposed 12 APAC indicators to assess and mitigate the individual-level health risks from air pollution. The individual-level health risk from air pollution was measured in terms of APAC index. In the study, the APAC indicators were first statistically validated based on data from panels of experts in medicine, health care, and the environment. The expert-validated APAC indicators were then transformed into a 12-question questionnaire to measure the individual-level APAC index, which was converted into an APAC grade for ease of interpretation. To assess the individual-level health risks from air pollution, the APAC grade was compared against the grading criteria which are based on 7-day average U.S. AQI levels.

SEM was used to validate the APAC indicators (i.e., A1–A12). In the exploratory factor analysis (EFA), the 12 APAC indicators were validated based on the experts' responses and then statistically classified into groups by APAC components. There were three EFA-classified APAC components: Components I, II, and III. The APAC indicators and components were further validated by confirmatory factor analysis (CFA) to determine the factor loadings and reliability of the indicators and components. The factor loading (between 0–1) indicates the degree of relevance of an APAC component or indicator to individual-level adaptive capacity to air pollution.

The findings indicated that the indicator A8 (take dietary supplements to reduce oxidative stress) had the highest indicator-level factor loading (0.797), followed by A4 (adopt diet regimens that lower oxidative stress) with the second-highest indicator-level factor loading (0.737). The adoption of A8 and A4 would thus significantly reduce the individual-level health risks related to air pollution. Interestingly, A7 (take a shower and change into new clothes upon returning to place of residence) is the practice that requires minimal effort in spite of the lowest indicator-level factor loading (0.389).

In essence, the proposed APAC-based self-assessment program could be adopted as an economical and efficient alternative to costly and complicated clinical assessment. Furthermore, subsequent research would comparatively investigate the self-assessment APAC index values and clinical assessment results to establish their correlation and determine the predictive capability of the APAC-based self-assessment program.

Supplementary Materials: The following are available online at <https://www.mdpi.com/article/10.3390/su132313141/s1>.

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