MODELLING THE COMMUNITY ADAPTIVE BEHAVIOUR TOWARDS AIR POLLUTION: A CONFIRMATORY FACTOR ANALYSIS WITH PLS-SEM

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Abstract

Air pollution has become a serious threat to public health due to the rapid economic development globally, and urban air pollution is thought to cause 1.3 million deaths annually. Urban areas have a huge potential for human exposure to the severity of air pollution and health concerns. Therefore, it is essential to advance our understanding of the factors influencing behaviour to provide compelling evidence for successful behavioural interventions and guidelines. Doing so will increase the practicality of public adaptation to the guidelines. Yet, little is known about the adaptive behaviour toward air pollution. This study aims to establish a predictive model of factors impacting the adaptative behaviour of urban Malaysians toward air quality. A deductive theory-generating research approach and a correlational research design were used in the development of a new ABR model. The following seven factors were tested: values (VAL), attitude (ATT), perceived vulnerability (PVL), perceived severity (PSV), self-efficacy (SEF), response efficacy (REF), and risk perception (RPN). Klang Valley served as the study area, and a multi-stage cluster sampling technique was used to select the respondents (n = 440) of a face-to-face questionnaire survey. In conjunction with PLS-SEM analyses, confirmatory factor analysis (CFA) was used to evaluate the structural models. The results demonstrated that PLS-SEM CFA is suitable for building a reliable structural model to examine community adaptive behaviour.

Keywords: Air Pollution, Adaptive behaviour; Confirmatory Factor Analysis

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INTRODUCTION

Air pollution is a mixture of harmful gases and particles released into the atmosphere due to either natural or human activities (Bai et al., 2018; Ferguson et al., 2020; Leh et al., 2020). While human activities are the primary cause of air pollution, humans and other creatures are the ones that suffer the repercussions of this pollution. Most empirical studies on air pollution have focused on metropolitan areas in developed nations (Chen et al., 2016; Dedoussi et al., 2020; Lu & Liu, 2015; Sun et al., 2018), yet the rapid urbanisation in developing nations may have a more profound impact (Manisalidis et al., 2020). Based on the findings from a national survey covering more than 4300 cities, World Health Organization (WHO) reports that more than 80% of the urban population resides in areas that do not comply with PM2.5 air quality guidelines (World Health Organization (WHO), 2020). Therefore, air pollution is anticipated to play a greater role in the association between urbanisation and health outcomes. This relationship may be particularly significant for rapidly developing economies and densely populated Asian nations, which are gradually exposed to poor air quality.

Previous studies have demonstrated that the negative impacts of pollution on human health are closely related to a polluted environment, which diminishes the quality of life (Mccarron, 2022; Tainio et al., 2021; Zhang et al., 2018). People's behavioural responses to air pollution may alter its effects, but this has yet to be identified in the literature (Ban et al., 2017; Id & Min, 2019). Generally, people substantially impact air quality, and therefore, their behavioural adaptations and responses will mitigate the effects of pollution. This study tackles the lack of insight into adaptive behaviour toward air pollution and the factors underlying the various behavioural responses, emphasising the significance of persuading people to reduce their exposure to air pollution and diminish the health risk and effects.

RESEARCH BACKGROUND

Due to the increasing number of motor vehicles, increased industrial activity (stationary), and transboundary pollution from neighbouring countries, air pollution has now emerged as one of Malaysia's most persistent environmental problems (Fadzly et al., 2018; Sahrir et al., 2019; Sentian et al., 2019). The increasing numbers of urban populations in the next decade highlight the need to investigate air pollution's source, variability, and impacts. However, assessing air quality data does not automatically lessen pollutant exposure and promote public health. Instead, the measure is the initial step in a multi-stage process of external and internal cues motivating and facilitating individual behaviour change to promote public health (Mccarron, 2022). For example, avoiding haze, staying indoors, and using facemasks can lessen air pollution.

Studies on air pollution in Malaysia have primarily concentrated on the atmospheric components of pollution, with a focus on quantifying the level and contaminants (Althuwaynee et al., 2020; Franklin, 2017; Sahrir et al., 2019; Zahari et al., 2016). However, there is little evidence on the social impact of pollution, and much research has not focused on adaptive behaviour towards air pollution. People can alter their behaviour to lessen the environmental effects because they appear to adapt to positive and negative life changes by altering their standards, goals, and expectations (Gifford & Nilsson, 2014). For example, Ruan et al. (2020) found that coping and threat appraisal leads to adaptive behaviour in their ability to cope with the risk. Therefore, the detrimental impacts of air pollution can be lessened with a greater knowledge of people's behavioural responses to poor air quality.

In 2011, the Department of Environment (DOE) Malaysia unveiled its five strategies under the "Clean Air Action Plan," which encouraged actions to create a more environmentally friendly industrial infrastructure, lower vehicle emissions, prevent haze from open-burning fires and forest fires, boost self-efficacy, and increase community engagement and awareness of air pollution (DOEM, 2013). As a result, urban Malaysians have begun small-scale personal protective behaviours, such as wearing protective masks and limiting outdoor activities to lower the risks of adverse health consequences from air pollution while they wait for regulations to enhance ambient air quality (De Pretto et al., 2015; Wong et al., 2017). However, given the negative impacts of air pollution, strategies must be developed to help people lower their daily exposure. The psychosocial perceptions of air pollution, environmental concerns, and environmental knowledge have all been mentioned in previous studies as factors influencing the individual-level response to haze episodes (Liu et al., 2018; Mirzaei-Alavijeh et al., 2020), but the effects of the interactions between multiple factors have received as little attention (Ban et al., 2017). Adaptive behaviour is still a developing idea that has not been conceptualised or thoroughly measured.

THEORETICAL BACKGROUND
The efficacy and extent to which an individual achieves the norms of personal independence and societal duties have been universally viewed as adaptive behaviour (Price et al., 2018). The combination of conceptual, social, and practical abilities that people develop to help them operate in their daily lives can also be defined as adaptive behaviour (Schulkin, 2011). However, the idea of adaptive behaviour, as noted in previous studies, is still in its infancy. The debate continues, particularly on how to define adaptive behaviour. Furthermore, explaining human behaviour in all its complexity is challenging, thus necessitating a theory that is centred on describing specific facts and linkages in the research.

Among the few well-known theories that analyse behaviour toward environmental risk are the theory of environmentally significant behaviour (TESB) (Stern, 2000), the theory of planned behaviour (TPB) (Ajzen, 1991), and the protection motivation theory (PMT) (Rogers, 1975). The social adaptation theory (SAT) (Kahle, 1984) is one of the key theories that explain cognitive functions such as values and attitude. This theory is pertinent to this study because it focuses on the adaptive behavioural reactions in the community to urban air quality. Consequently, the PMT and SAT theories could be used to explain how the community in this study adapts to urban air pollution. The SAT and PMT are also excellent illustrations of a theory that even academics from other fields, like psychology and sociology, may use to explore various empirical occurrences. These theories adhere to the terminology and concepts of studying adaptive behaviour.
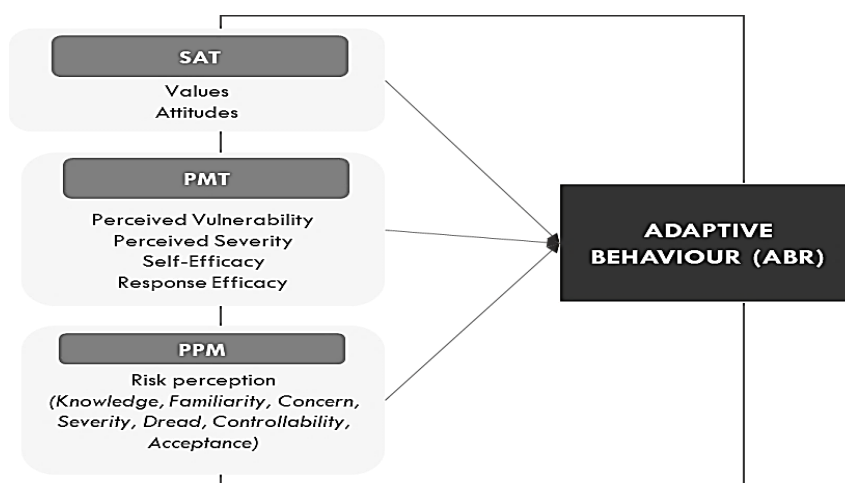

Figure 1: Conceptual Framework

The SAT theory, though is more frequently applied to marketing and consumer behaviour (Coelho et al., 2014), can also be used as a framework for this study to present novel insights into how people adapt to their environments. For example, in terms of cognitive function, attitude (ATT) and values (VAL) are the variables that can explain adaptations to air pollution. Although the PMT originates from health psychology and is frequently used as a framework for comprehending reactions to triggers that make people aware of possible risks, the association between protective behaviour in adaptation behaviour has been supported by considerable research (Koerth et al., 2013). This theory has two elements–threat and coping appraisal–which can be alienated into perceived

vulnerability (PVL), perceived severity (PSV), self-efficacy (SEF), and response efficacy (REF). How the general public perceives and accepts the risk of air pollution may influence how an individual behaves (Huang et al., 2017). Therefore, risk perception (RPN), considered as The Psychometric Paradigm (PPM) (Slovic, 1987), is a significant variable in adaptive behaviour toward air pollution. The seven variables constitute the foundation of the conceptual framework of the Adaptive Behaviour (ABR) model for air pollution in the urban community. Figure 1 illustrates the conceptual framework for this study.

METHODOLOGY
A descriptive or correlational research study was chosen after the study's objectives were established, and the instrument employed was a face-to-face questionnaire, as adopted in the previous studies (Bazrbachi et al., 2017; Zhao et al., 2018). The focus was placed on Klang Valley which comprise cities that have experienced substantial expansion and development over time, leading to the deterioration of the local air pollution. The Klang Valley's households (residential units) served as the basis for defining the population for this study. A multi-stage cluster sampling technique was primarily used to divide the study area into smaller areas until the sampling units were attained. The computed sample size was found to be 400 samples from the entire Klang Valley population using the Yamane's (1967) method for sample size, with an error of 5% and a confidence level of 95%. A total of 440 samples was calculated to be the appropriate sample size with a 10% margin of error (Suresh & Chandrashekara, 2012) to prevent unattended or missing questionnaires.

A three-step sampling method was used when population data for a specific urban area was available. The first step was to choose a district inside the city. All the communities within this district with more than 5,000 residents were used as the primary sample units based on the proportion to population size (PPS). In the subsequent stage, one of the communities was randomly selected, and 440 of its houses were then chosen using a systematic sampling technique. Next, to obtain the skip interval pattern for the sampling frame, the region was divided into many areas, and the *kth* element was calculated by dividing the sample size by the population (dwelling units). Finally, residents of households above 18 who could independently complete the questionnaire were requested to do so. The questionnaire was designed with three sections and 81 items, including 13 in the demographic sections (refer to Table 1).

Table 1: Items based on section

Section	Dimension	Code	Number of items
	ABQ		
Section I – Part A	Concern behaviour	ABR	6

Section I – Part B	Daily normal behaviour		7
Section I – Part C	Protective behaviour		2
	SAQ		
Section II – Part A	Values	VAL	10
Section II – Part B	Attitudes	ATT	8
	PMQ		
Section II – Part C	Perceived vulnerability	PVL	6
Section II – Part D	Perceived severity	PSV	6
Section II – Part E	Self-efficacy	SEF	8
Section II – Part F	Response efficacy	REF	8
	RPQ		
Section II – Part G	Risk Perception	RPN	7
	Demographic Questionnaire		
Section III	Demographic Information		10
	Self-reported experience		2
	Health status		1
	Total items		**81**

Statistical analysis of the survey data was carried out using IBM SPSS software. A partial least square (PLS) analysis was performed using the SmartPLS programme. To overcome the shortcomings of the first-generation approach, such as multiple regression, researchers now frequently adopt second-generation techniques, i.e. structural equation modelling (SEM), to incorporate unobservable variables that are indirectly quantified by indicator variables. Multiple regression, logistic regression, analysis of variance, and methods like exploratory and confirmatory factor analyses are the main components of the first-generation approaches (Hair et al., 2017). However, when the research goal is to predict and explain the variance in important target variables using several explanatory constructs, the PLS-SEM is very appealing. The phenomenon under study is the testing of VAL, ATT, PVL, PSV, SEF, REF, and RPN, which lead to the adaptive behaviour of the community.

RESULTS
Confirmatory factor analysis (CFA) is a unique type of factor analysis used most frequently in social research in statistics. By estimating the causal relationship between the relevant variables (given the variances, covariances, or means from the observed variables), the CFA is used to assess the validity and reliability of a measurement model (Goodboy & Kline, 2017). To establish the causal relationship between the latent variables in this study, the SEM adopted combined CFA and path analysis. Prior to testing the hypothesis, a CFA was conducted to determine if the framework of determinants fits the acquired data. The CFA was conducted by evaluating the measurement model (internal consistency reliability,

convergent validity, and discriminant validity threshold). All Cronbach's alpha values ranged between 0.756 and 0.912, and the composite reliability value ranged between 0.839 and 0.929, exceeding the specified threshold values (Chin, 1998b; Nunnally & Bernstein, 1994) as exemplified in Table 2.

Table 2: Cronbach's Alpha and Composite Reliability

	Cronbach's Alpha (α)	Composite Reliability (CR)
ABR	0.869	0.896
VAL	0.858	0.892
ATT	0.876	0.881
PVL	0.848	0.864
PSV	0.756	0.839
SEF	0.912	0.929
REF	0.881	0.895
RPN	0.796	0.859

KEY: **ABR** = Adaptive Behaviour, **VAL** = Values, **ATT** = Attitude, **PVL**= Perceived Vulnerability, **PSV**= Perceived Severity, **SEF** = Self-efficacy, **REF** = Response Efficacy, **RPN** = Risk Perception

A variable is considered to have convergent validity if three conditions are met: (1) all individual items must exceed 0.7; (2) the second composite reliability value must be greater than 0.7; and (3) the AVE value must be greater than 0.5 (Fornell & Larcker, 1981). Table 3 indicates a composite reliability of greater than 0.70 (the minimum criterion of reliability), thus confirming that the research instrument meets the standards for internal consistency. While the numerous loadings are less than 0.7, the indicators with loadings less than 0.708 may be preserved if an AVE of at least 0.5 is reached, as prescribed by Ramayah et al. (2018). As indicated from the findings, all the measurement items for the constructs meet the threshold for convergent validity.

Table 3: Discriminant Validity using Fornell-Larcker Criterion

	ABR	ATT	PSV	PVL	REF	RPN	SEF	VAL
ABR	0.704							
ATT	0.169	0.723						
PSV	0.458	0.039	0.726					
PVL	0.189	-0.042	0.139	0.725				
REF	-0.355	-0.563	-0.283	0.047	0.718			
RPN	0.230	-0.001	0.140	0.303	0.002	0.780		
SEF	0.658	0.267	0.452	0.060	-0.581	0.170	0.787	
VAL	0.695	0.375	0.341	0.139	-0.548	0.147	0.631	0.737

Note: Diagonals represent the square root of the AVE while the off-diagonals represent the correlation

The third method for evaluating discriminant validity is the HTMT, an improved criterion proposed by Henseler et al. (2015). If the AVE of the latent

variable is greater than the squared correlations of the latent variable with other model constructs, discriminant validity is established. The outcome of HTMT inference demonstrates that the confidence interval did not have a value of 1 on any of the constructs, thus supporting the discriminant validity. As shown in Table 4, all the values satisfy the HTMT requirement. Several variables were eliminated from the model since their loading values were low and affected other measurement aspects. Eliminating these variables did not cause the model to surpass the specified threshold.

Table 4: HTMT Criterion

	ABR	**ATT**	**PSV**	**PVL**	**REF**	**RPN**	**SEF**	**VAL**
ABR								
ATT	0.173							
PSV	0.530	0.232						
PVL	0.167	0.069	0.189					
REF	0.340	0.745	0.265	0.082				
RPN	0.228	0.086	0.179	0.349	0.063			
SEF	0.735	0.294	0.507	0.069	0.589	0.178		
VAL	0.773	0.444	0.370	0.116	0.633	0.154	0.712	

KEY: **ABR** = Adaptive Behaviour, **VAL** = Values, **ATT** = Attitude, **PVL**= Perceived Vulnerability, **PSV**= Perceived Severity, **SEF** = Self-efficacy, **REF** = Response Efficacy, **RPN** = Risk Perception

DISCUSSION
The main objective of this study was to develop and validate the ABR model to measure the factors driving community adaptive behavioural responses towards air pollution. Intriguingly, the results indicate that the CFA generated the best model fit in terms of factor loadings. The CFA could confirm the reflective measurement model and reflect the use of PLS-SEM to maximise the explained variance of endogenous latent constructs and predict the ABR model in this study. In a reflective measurement model, the indicators of a construct are attributed to that construct. Testing the measurement model is the first step in a PLS path modelling analysis. It examines the extent to which the study items measure what should be measured, their accuracy in representing each construct, and whether or not they meet the standards for validity. One of the contributions of this study is the use of an approach for developing and validating a prediction model by reviewing theories and literature on adaptive behaviour. This method allowed the researcher to identify similarities and differences across diverse fields. By revealing the significant variables constructions of the model, this study contributes valuable information to the development and implementation of air pollution protection guidelines. Consequently, by identifying the key predictors of the community's current behaviour, this research contributes to developing the pillars of an effective and sustainable society.

CONCLUSIONS

This study conveys its theoretical and practical contributions by establishing and validating the ABR model to measure the adaptive behaviour of a community towards air pollution. Regarding the key predictors of adaptive behaviour, the literature indicates little consensus in elucidating the position. The findings of the study, however, demonstrate that the variables chosen at the beginning of the study are reliable predictors for identifying the factors that influence behavioural adaptation among the urban population of Malaysia. Future studies may advance the current study, mindful that the study was conducted in an urban setting, where the sample was collected. This will restrict its applicability to countries with distinct cultural and geographical settings. Future studies may also test the predictability of the model in other countries with different cultural settings to identify any potential cultural and setting-based stimulus on adaptive behaviour towards air quality.

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