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Research Paper

Structural Equation Model-Based Selection and Strength Co-Relation of Variables for Work Performance Efficiency Under Traffic Noise Exposure

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In this work, we integrated exploratory factor analysis (EFA) followed by structural equation modelling (SEM) to assess the work performance efficiency under the traffic noise environment for open shutter shopkeepers in the Indian urban context. 706 valid questionnaire responses by personal interviews in local language were collected from open shutter shopkeepers exposed to noise level (L_{eq}) of 77 dBA for 12 to 14 hours daily. The questionnaire was prepared based on demographics, environmental conditions, and primary effects of noise pollution. Among which four common latent factors which summaries 17 questionnaire response items were obtained by exploratory factor analysis, which are "Impacts of noise" (IM), "Environmental conditions" (EC), "Personal characteristics" (PC) and "Work efficiency" (WE). The associations between the individual latent factors were studied by the structural equation model method in AMOS software. Validation of the constructed model was carried out by testing the proposed hypothesis as well as goodness-of-fit indices like Absolute fit, Incremental fit, and Parsimonious fit indices. The effect of specific latent factors derived on the work efficiency of shopkeepers in the noisy area was characterized by the path coefficients estimated in the SEM model. It was found that work performance efficiency (WE) was greatly influenced by the primary impacts of noise pollution like annoyance, stress, interference in spoken communication, which was associated with the latent factor "Impacts of noise" (IM) with a path coefficient of 0.931. The second latent factor "Environmental conditions" (EC), which was associated with parameters like ambient temperature and humidity, showed less path coefficient of 0.153. And lastly, a latent factor called "Personal characteristics" (PC) associated with age, experience, education, showed the least path coefficient of 0.05. The work efficiency of open shutter shopkeepers working in a highly noisy commercial area is profoundly affected by the prominent effects of noise pollution and least affected by ambient environmental conditions as well as their personal characteristics. The developed model clarified some casual relationships among complex systems in the study of noise exposure on individuals n tier 2 cities in the Indian context and may help other researchers to study of tier I and tier III cities.

Keywords: work efficiency; traffic noise pollution; exploratory factor analysis; structural equation model; AMOS software.

1. Introduction

One of the essential occupations spread across the world is shopkeeping. In the Indian context, these shops include clothing stores, small eateries, medical stores, Xerox shops, general stores, stationaries, etc. established along busy urban roads and shopping districts. In countries like India, millions of people make their living from the shops situated on the main roadsides or primary streets for maximum sales. These main roads and primary streets have peak traffic hours during morning and evening time, having noise levels as high as 93 dBA at peak traffic hours (9 am – 11 am and 5 pm – 8 pm) due to the honking of horns and up to 70 dBA at non-peak traffic hours (Yadav, Tandel, 2019). Generally opening time for shops is from 8 am to 10 am and closing time is from 8 pm to 10 pm, so these shops' owners are exposed to high traffic noise for 12 to 14 hours daily which is undoubtedly exceeding occupational health and safety (OSHA) standards (Mallick *et al.*, 2009). Hence, it is imperative to study various effects of noise on these shopkeepers.

Two arithmetical methods, exploratory factor analysis (EFA) and structural equation modelling (SEM) have come into the light in recent years due to its vast use in identifying and assessing the relations in hypothetical models (Liu *et al.*, 2018). Precisely, EFA is beneficial in the case of studies based on direct interview responses (Finch, West, 1997). It helps in recognizing the relationships among variables acquired from questionnaire items without past knowledge features and the patterns of the acquired variables (Finch, West, 1997). Secondly, the SEM approach is advantageous in studying complicated relationships between measured variables (Voth-Gaeddert, Oerther, 2014) as well as SEM simultaneously calculates all required coefficients in the system (Xiong *et al.*, 2015).

In this research article, we propose an integrated and systematic method by using the advantages of EFA and SEM to extract out, analyze, and verify all possible factors affecting the work efficiency of open shutter shopkeepers under the influence of traffic noise pollution.

2. Work efficiency and noise pollution

Throughout the last five decades, noise pollution levels in the world have been increased (Dzhambov, Dimitrova, 2018). Especially in India, due to population explosion, rapid industrializing, and high-density traffic, the noise levels are increasing day by day (Tandel, Macwan, 2017). The negative impacts of such high noise are now reflecting in our day to day life. Significant adverse effects of noise are annoyance, headaches, interference in spoken communication, noise-induced hearing loss, stress, social behaviour and a decrease in work efficiency (WHO, 2011). In the case of industrial noise, the work efficiency of industrial workers decreases in high or impulsive noise (Zaheeruddin, 2006). Several types of research have been done to explore the effects of industrial noise on workers (Banerjee, 2012) but less researches have been done on the effect of traffic noise on the day to day life activities. The risk of hypertension and heart disease is increased due to continuous exposure to noise for more than 12 hours (Seidler *et al.*, 2016). High blood pressure was also recorded as an effect of traffic noise exposure in the United Kingdom (Tonne *et al.*, 2015; Halonen *et al.*, 2017).

As we talk about an individual's work efficiency and productivity, noise pollution in the surroundings plays a vital role (Babisch *et al.*, 2013). The work efficiency of an individual is reduced by annoyance, stress, and interference in spoken communication (Pal, Bhattacharya, 2012). Work efficiency is also highly dependent on the type of task an individual is performing (Zaheeruddin, Jain, 2008). Environmental conditions can also have an effect on human work performance (Bell, 1980; Singh *et al.*, 2007). The age of individuals and their daily exposure to noise also play an essential role in assessing work efficiency (Zaheeruddin, Garima, 2006). Hence as mentioned in the introduction, the study focuses on open shutter shop workers as they are exposed to high traffic noise pollution for more than 12 hours daily.

3. Methodology

3.1. Background

Structural equation modelling (SEM) is a type of system of fundamental modelling that comprises a varied set of statistical methods, computer algorithms, mathematical models, and that fits links of hypotheses to data (Hair *et al.*, 2010). Using SEM has numerous advantages. The first one is that SEM analyses complicated associations between variables, as well as it includes those that are unobserved or hypothetical (i.e. latent variables) (Bag, 2015). The second one is that SEM calculates all coefficients in the system at the same time; hence, it permits the investigator to evaluate the implication and importance of any specific relationship in the setting of the entire model (Mallick *et al.*, 2009). Also, the constructed model can be statistically verified in an instantaneous analysis of the full system of variables to check the validity of the model (Dion, 2008).

Exploratory factor analysis (EFA) is a method from factor analysis whose principal goal is to recognize the underlying associations between measured variables (Thompson, 2004). It finds out a set of latent or unobserved parameters from observed variables, and it is highly beneficial when there is no previous hypothesis of the factors or the patterns of observed variables (Finch, West, 1997). Thus, integrating EFA and SEM is very useful in studies based on the questionnaire where a number of observed variables are high (Liu *et al.*, 2018). Before using SEM, one should do EFA to identify the number of latent factors.

3.2. Data collection

The study was done in Surat city (Gujarat), India's tenth largest city, which has an estimated population of 4.6 million-plus at present. An incomprehensible population growth rate of 76.02% was observed over the last decade as a byproduct of rapid industrialization (Tandel, Macwan, 2017). For this study, the Chowk Bazar area in the central zone was selected. The area is one of the most important and busy commercial areas in Surat city as all kinds of shops reside in the vicinity. The area has very high traffic volume since it contains important collector roads.

Noise measurement was done using the KIMO DS 300 class 2 sound level meter. To carry out noise monitoring, the "Noise monitoring protocol" given by the Central Pollution Control Board (CPCB) in the year 2015 was followed (CPCB, 2015). Meteorological data required for the study was provided by two organizations: Indian Meteorological Department, Surat, and Surat Climate Change Trust (SCCT), Surat. A questionnaire of a total of 24 items was designed to assess the exposure effects of traffic noise. The questionnaire was divided into two parts, first part observed personal characteristics like age, working years, daily working hours, etc., and the second part covered prominent noise exposure effects like headaches, annoyance, interference in spoken communication, the effect of high temperature and humidity, stress etc. The questionnaire survey was done using personal interviews and answers were collected using a five-point Likert's scale ranging from "1" for "very low" to "5" for "very high". The interviews were taken in the local language as the education level of people in the area was low, as well as to make the interaction more productive. The shop workers facing an adverse effect of noise gave high scale value accordingly. In addition to noise exposure effects, two more questions were included in the questionnaire, i.e. "Are you satisfied with working in this area?" and "When you are not working in a noisy area, what is your level of comfort?" to determine how respondents perceive the impact of noise pollution in general and its significant effects on their health. These two questions were also represented with the Likert scale (i.e. 1 signifies profound influence and 5 signifies strong influence). For the determination of sample size for this study formula given by Krejcie and Morgan was used (Chuan, 2006). The minimum number of sample size obtained from the equation is 384, and about 706 responses were collected.

4. Results and discussions

4.1. Noise monitoring

With the help of sound level meter, different points within the study area were monitored for noise levels. It was carried out in ten locations in five different stretches. The monitoring was carried out from 9 am to 9 pm, i.e. for 12 hours as the average opening time for shops in the study area is 9 am and the average closing time is 9 pm. Also, according to the noise monitoring protocol given by the Central Pollution Control Board, India (CPCB) a minimum of 12 hours' readings must be taken for day time monitoring. The noise level meter was kept on the tripod stand such that its microphone sensor was at an elevation of 1.2 to 1.5 meters above the ground, which is the average height of ears. Figure 1 shows equivalent, maximum and minimum noise levels in selected locations. The equivalent noise levels in all stretches are above 77 dBA. It is evidently crossing the standards given by the Ministry of Environment and Forest (MoEF) for the commercial area for day time, which is 65 dBA.

4.2. Exploratory factor analysis (EFA)

Exploratory Factor Analysis (EFA) was done with data collected by a questionnaire survey to assess data distribution, correlations in variables, and mainly to find our unobserved or latent factors dependent on observed variables. EFA is used for data summarization and extracts necessary information with the help of a small number of units to characterize the original data and understand the complicated associations between variables (Thompson, 2004). Hence EFA can be useful to recognize data patterns in questionnaires, reorganize the data where suitable, and clarify the measured variables in the questionnaire into an optimum number of extracted factors. In the current study, EFA was used to find out the common factors affecting work efficiency from observed variables in the questionnaire (Liu *et al.*, 2018). The EFA was carried out in the SPSS software suite with the extraction method as principle component analysis, convergence iterations were set to 30, and the rotation method chosen was varimax (Costello, Osborne, 2005).

4.2.1. Kaiser-Meyer-Olkin test and Bartlett test

The Kaiser-Meyer-Olkin (KMO) test and the Bartlett test should be carried out to ensure that the initial

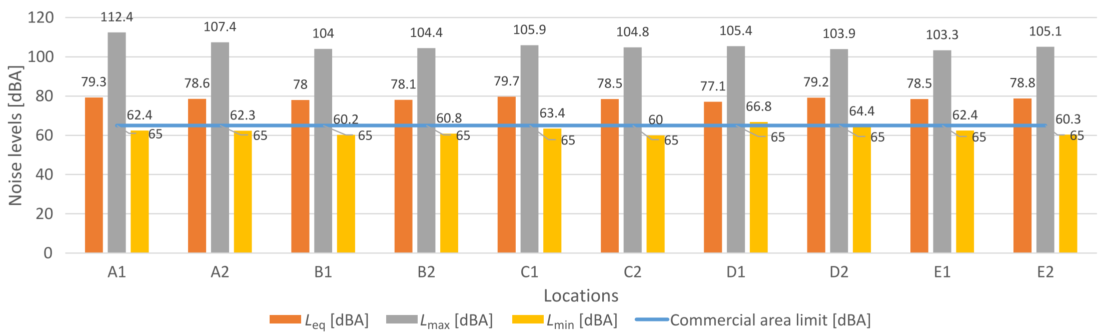

Fig. 1. Graph showing maximum, minimum, and equivalent noise levels in all locations.

variables taken into consideration have a strong correlation. The tests should give good results. Notably, the KMO test primarily ensures if the collected data is satisfactorily distributed in the sample considered for the EFA. The KMO coefficient should be above 0.7 for a good correlation (Patel, Jha, 2016). The Bartlett test is used to identify if the identity matrix is a correlation matrix; in such cases, EFA is not valid. As shown in Table 1, the KMO value calculated for the data was 0.785, which ensured that the collected data were appropriate for EFA. Also, Bartlett's test's significance level came as 0.000, which was smaller than 0.01. Hence by these two tests, it is proven that the collected data can be used for latent factor extraction using EFA (Liu *et al.*, 2018).

Table 1. Kaiser-Meyer-Olkin test and Bartlett test (original).

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.785
Bartlett's test of sphericity	Approx. chi-square	4279.223
	Df	91
	Sig. level	0.000

4.2.2. Exploratory factor extraction

The correlation coefficient between a separate variable and its common factor is represented as factor loadings. The data was run for EFA by choosing the principal component factor analysis extraction method. It merges variables with high factor loadings to the specific latent factor. A solution of a total of four latent factors was extracted, and showed a total variance of 64.483%, as shown in Table 2. The number of latent factors extracted by EFA, whose eigenvalue was more than 1, was chosen.

To get a better understanding of the extracted factors, a variable with a factor loading of less than 0.45 was taken as the weak variable. It should not be considered for study (Bowden, Wang, 2006). Table 3 shows the original rotated matrix of factor loadings of 4 latent factors solution obtained. Table 4 shows the four extracted latent factors with their respective factor loadings after rotating the correlation matrix. In the case of a variable showing a correlation to two or more latent factors, the correlation matrix is rotated to get a simplified solution (Hair *et al.*, 2010). Each extracted common factor was given a label/name to indicate the mutual and possible characteristics for its better understanding as shown in Table 4. The same extracted common factors are further tested by the Structural equation modelling method. The notations given to the measured variables are not in order in Table 4 as they are arranged by its common latent factors, which are given below.

Factor 1 (IM) accounted for a total 31.850% of the total variance as shown in Table 4 with eight variables, i.e. headache due to noise pollution (X12), hearing problem at work due to noise (X13), interference in spoken communication due to noise (X14), an-

Table 2. Explanation of total variance in the EFA (original).

Total variance explained									
Component	Initial eigenvalues			Extracted sum of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative [%]	Total	% of variance	Cumulative [%]	Total	% of variance	Cumulative [%]
1	4.446	31.758	31.758	4.446	31.758	31.758	3.653	26.091	26.091
2	1.832	13.088	44.846	1.832	13.088	44.846	2.472	17.659	43.750
3	1.723	12.309	57.155	1.723	12.309	57.155	1.865	13.322	57.072
4	1.026	7.327	64.483	1.026	7.327	64.483	1.038	7.411	64.483
5	0.914	6.526	71.009						
6	0.782	5.583	76.592						
7	0.733	5.237	81.829						
8	0.578	4.130	85.959						
9	0.474	3.383	89.342						
10	0.465	3.323	92.664						
11	0.410	2.929	95.594						
12	0.327	2.338	97.932						
13	0.207	1.478	99.409						
14	0.083	0.591	100.000						
Extraction Method: Principal Component Analysis.									

Table 3. Rotated component matrix (original).

Observed variables	Component			
	1	2	3	4
Headache due to noise pollution	0.764			
Hearing problem at work due to noise	0.712			
Interference in spoken communication due to noise	0.743			
Annoyance due to noise	0.660			
Loss of concentration due to noise	0.615			
Stress due to noise	0.701			
Feeling of exhaustion due to noise	0.554	0.513		
Customer rush	0.501			
Effect of temperature		0.918		
Effect of humidity		0.926		
Daily working hours		0.466	0.457	
Age			0.923	
Working Years (work experience in the area)			0.930	
Education Level			0.712	
Difficulty performing task due to noise				0.523
Level of comfort when not working in noise				0.688
Job satisfaction				0.766
Extraction method: principal component analysis Rotation method: Varimax with Kaiser normalization (rotation converged in 5 iterations)				

Table 4. Factor load matrix after rotation and the extracted four common factors (original).

Variables		Loadings after rotation	Extracted common factor
Notation	Observed variable		
X12	Headache due to noise pollution	0.764	IM: impacts of noise pollution
X13	Hearing problem on work due to noise	0.712	
X14	Interference in spoken communication due to noise	0.743	
X15	Annoyance due to noise	0.660	
X16	Loss of concentration due to noise	0.615	
X17	Stress due to noise	0.701	
X18	Feeling of exhaustion due to noise	0.554	
X19	Customer rush	0.501	
X21	Effect of temperature	0.918	EC: environmental condition
X22	Effect of humidity	0.926	
X3	Daily working hours	0.466	
X1	Age	0.923	PC: personal characteristics
X2	Working Years (work experience in the area)	0.930	
X5	Education level	0.712	
X7	Difficulty performing task due to noise	0.523	WE: work efficiency
X23	Level of comfort when not working in noise	0.688	
X24	Job satisfaction	0.766	

noyance due to noise (X15), loss of concentration due to noise (X16), stress due to noise (X17), feeling of exhaustion due to noise (X18), and customer rush (X19). All these variables denote the effects of noise pollution; hence the factor was named "Impacts of noise pollution (IM)" as shown in Table 4.

Factor 2 (EC) accounted for 13.343% of the total variance, as shown in Table 4, with three variables, i.e. effect of temperature (X21), effect of humidity (X22), and daily working hours (X3). This factor was named "Environmental condition (EC)" as shown in Table 4.

Factor 3 (PC) accounted for 12.407% of the total variance, as shown in Table 4, with three variables, i.e. age (X1), working years (work experience in the area) (X2), and education level (X3). All these variables denote personal information of respondents; hence, this factor was named "Personal characteristics (PC)" as shown in Table 4.

Factor 4 (WE) accounted for 7.336% of the total variance, as shown in Table 4, with three variables, i.e. difficulty performing task due to noise (X7), level of comfort when not working in noise (X23), and job satisfaction (X24). All these variables are mostly related to the performance of the respondents. Hence, it was named "Work efficiency (WE)" as shown in Table 4.

4.3. Structural equation modelling (SEM)

The interrelations between non-acoustical factors mentioned above have not been entirely understood yet. The relation between noise exposure and work efficiency can be better understood by the above mentioned or considered measured variables. The usual method to assess the influence on work efficiency is by non-acoustical variables with the help of multiple regression analysis or of correlational analysis. The correlation analysis just gives statistics about simple relations, but regression analysis is categorized by limitations as well. For example, it is not possible to measure unobserved indirect and mutual effects (Pennig, Schady, 2014).

On the other hand, structural equation modelling (SEM) is a more appropriate method to study and understand complicated multiple dependent associations by studying a number of hypotheses considered in a system or model (Ryu *et al.*, 2017). It exams primary or initial hypothetical theory-driven relationships with latent factors with their observed variables. This cannot be achieved by regression analysis. Latent factors represent hypothetical relationships as well as constructs that cannot be directly measured. These constructs are presumed to be determined only with measured variables as their indicators; for example questions asked in the questionnaire survey are served as measured variables. This unique quality of SEM permits to test a number of hypotheses about constructed latent factors and their interrelationships. In SEM, the latent factors considered can be used as predictors or inputs as well as outcomes or targeted output (Pennig, Schady, 2014). So far, very few researchers have used SEM to assess entire system models of the complicated direct and indirect relationships among non-acoustical parameters with the effects of traffic noise.

4.3.1. Model hypotheses

In SEM, a model hypothesis is one of the crucial steps (Xia *et al.*, 2012). As explained in the previous section, exploratory factor analysis (EFA) provides a basis for understanding the interrelationships to develop the measurement and structural models for SEM. To assess the interactions between the extracted common factors, as given in Table 4, the following hypotheses were established:

Hypothesis 1: IN (Impacts of noise pollution) affects WE (Work efficiency);
Hypothesis 2: EC (Environmental conditions) affects WE (Work efficiency);
Hypothesis 3: PC (Personal characteristics) affects WE (Work efficiency);
Hypothesis 4: IN and EC affect each other;
Hypothesis 5: IN and PC affect each other;
Hypothesis 6: EC and PC affect each other.

4.3.2. Measurement model

It is essential to build the measurement model before the actual structural model showing path coefficients (Hair *et al.*, 2010). To assess the relationship among the measured variables and the extracted latent factors AMOS software was used. The hypotheses given above were analyzed in the software "AMOS" with an SEM package using the collected data. Table 4 shows that four measurement models were needed to assess the exposure effect of noise pollution on work efficiency. For example, the measurement model of the latent variable IN (Impacts of noise pollution) consists of 8 observed variables, i.e. headache due to noise pollution (X12), hearing problem at work due to noise (X13), interference in spoken communication due to noise (X14), annoyance due to noise (X15), loss of concentration due to noise (X16), stress due to noise (X17), feeling of exhaustion due to noise (X18) and customer rush (X19). The overall measurement model made for the SEM analysis is shown in Fig. 2.

4.3.3. Structural model

The structural model represents all regression equation models as it explains the amount of unexplained and explained variance and hence, describes the relationships among the latent factors. With the help of the measurement model built, a structural equation model comprising both the structural model and measurement model was then constructed to inspect the assumed relationships among the four latent factors.

With the help of presumed hypotheses and data collected, the four common factors were connected to understand the exposure effects of noise, and their impacts were examined. A multi-dimensional model must have satisfactory legitimacy in both combination and separation so as to give the best fit whose path coefficients could make great forecasts. (Liu *et al.*, 2018). Figure 3 displays the initial SEM that combined the structural model and measurement model.

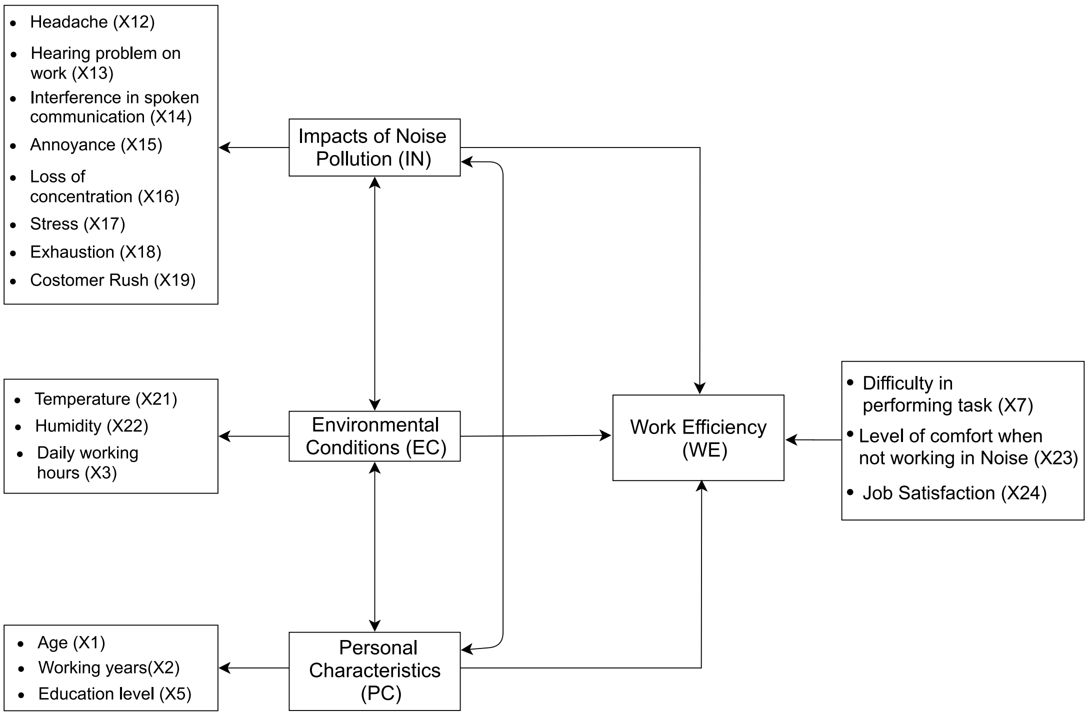

Fig. 2. Graphical representation of the initial hypothetical measurement model.

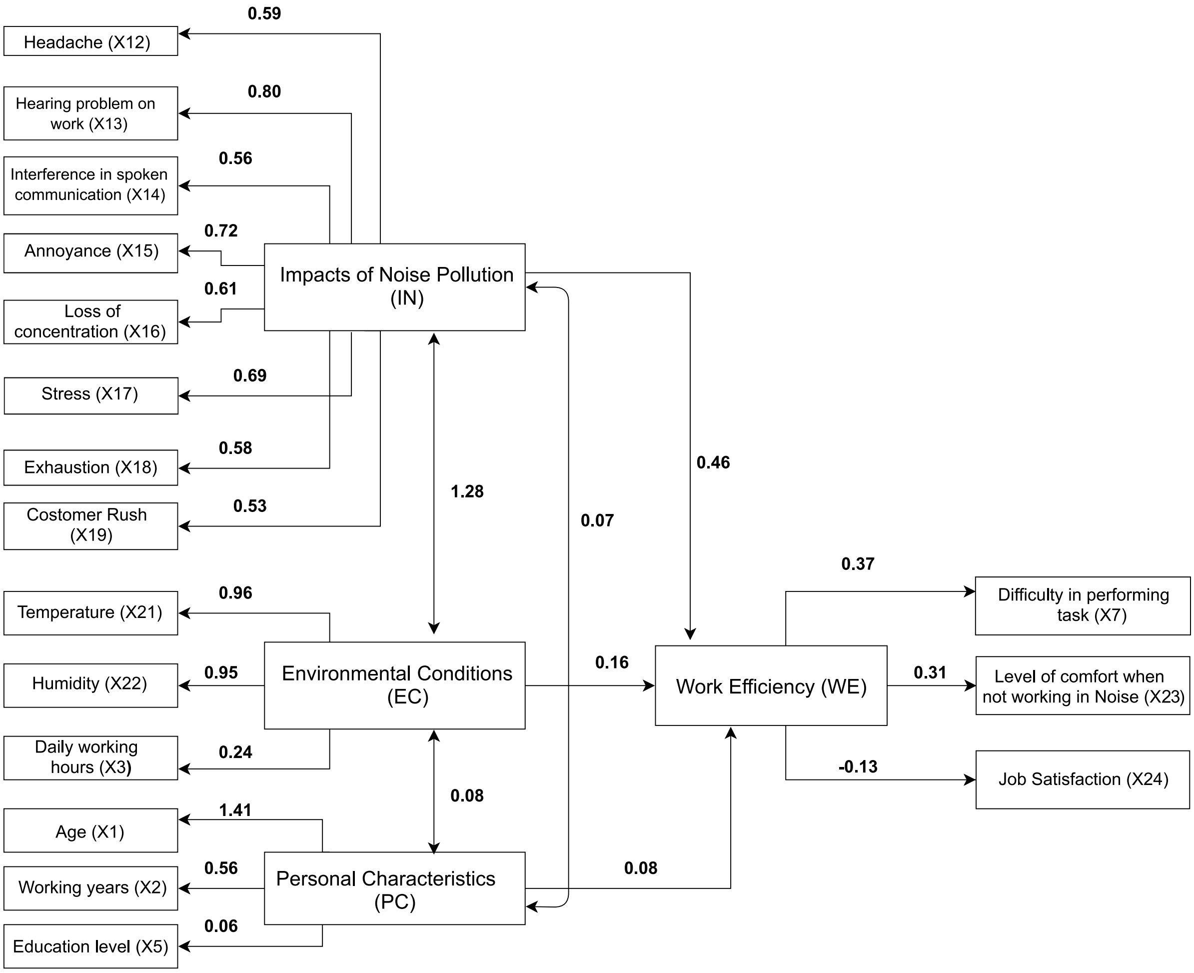

Fig. 3. Initial structural equation model with standardized estimates.

4.3.4. Hypothesis test analysis

Table 5 shows the regression weights of the initial model. When the significance level is less than 0.05, only then a hypothesis can be accepted. Hence, the hypothesis H5 and H6 were rejected as they had a significance value (p) of 0.123 and 0.127, respectively.

To validate the fitness of the structural model, all statistical coefficients in the anticipated model must be adequately assessed. This can be attained by a variety of sets of the goodness of fit indices available. Precisely for the structural equation model, absolute fit indices, incremental fit indices, and parsimonious fit indices are available (Hair *et al.*, 2010). SEM model should satisfy standards given by these indices. Several numbers of indices were chosen from the mentioned goodness of fit indices. Table 6 shows the goodness of fit of the initial structural equation model. Among all indices, only incremental fir indices and parsimonious fit indices were close to fit. Others, i.e. absolute fit indices, were not fit. It shows that the model needs to be improvised to get more indices fit.

To improve the model, series of attempts were made. In each attempt, one or two measured variables were omitted, and the results were checked (Chinda, Mohamed, 2008). Figure 4 shows the most optimized (revised) model, which had the highest number of the goodness of fit. Two measured variables, namely "hearing problem due to noise (X13)" and "job satisfaction (X24)", were omitted in the revised model. The reason behind the omitting of "hearing problem due to noise (X13)" in the latent factor "impacts of noise pollution (IN)" is, that it has another measured variable namely "interference with spoken communication

Table 5. Regression weights in the initial structural equation model (original).

Hypothesis	Regression weights				Test results
	Estimate	Standard error	Critical error	Significance level (p)	
H1: IN (Impacts of noise pollution) affects WE (Work efficiency)	0.993	0.100	9.884	*	Accepted
H2: EC (Environmental conditions) affects WE (Work efficiency)	0.346	0.172	2.010	0.044	Accepted
H3: PC (Personal characteristics) affects WE (Work efficiency)	−0.042	0.019	−2.219	0.026	Accepted
H4: IN and EC affect each other	0.36	0.007	5.170	*	Accepted
H5: IN and PC affect each other	0.010	0.017	1.525	0.123	Rejected
H6: EC and PC affect each other	0.790	0.007	1.540	0.127	Rejected

* $p < 0.001$.

Table 6. The goodness of fit of the initial structural equation model (original).

Type	Index	Fit standards of fitness	Obtained value	Result
Absolute fit	Chi-square	As low as possible	743.8	Good Fit
	CMIN/DF	Between 2 to 5	6.502	Not fit
	RMR	<0.05, good fit	0.066	Not fit
	RMSEA	<0.08, not bad fit; <0.05, good fit	0.089	Close to fit
	GFI	>0.90, good fit	0.888	Close to fit
Incremental fit	NFI	>0.90, good fit	0.850	Close to fit
	RFI	>0.90, good fit	0.820	Close to fit
	IFI	>0.90, good fit	0.870	Close to fit
	TLI	>0.90, good fit	0.843	Close to fit
	CFI	>0.90, good fit	0.870	Close to fit
Parsimonious fit	PGFI	>0.50, good fit	0.831	Fit
	PNFI	>0.50, good fit	0.707	Fit
	PCFI	>0.50, good fit	0.723	Fit

Note: AGFI – adjusted goodness-of-fit index; CFI – comparative fit index; GFI – goodness-of-fit index; IFI – incremental fit index; NFI – normed fit index; PCFI – parsimony comparative fit index; PGFI – parsimony goodness-of-fit index; PNFI – parsimony normed-fit index; RFI – relative fit index; RMR – root mean square residual; RMSEA – root mean square error of approximation; TLI – Tucker-Lewis index.

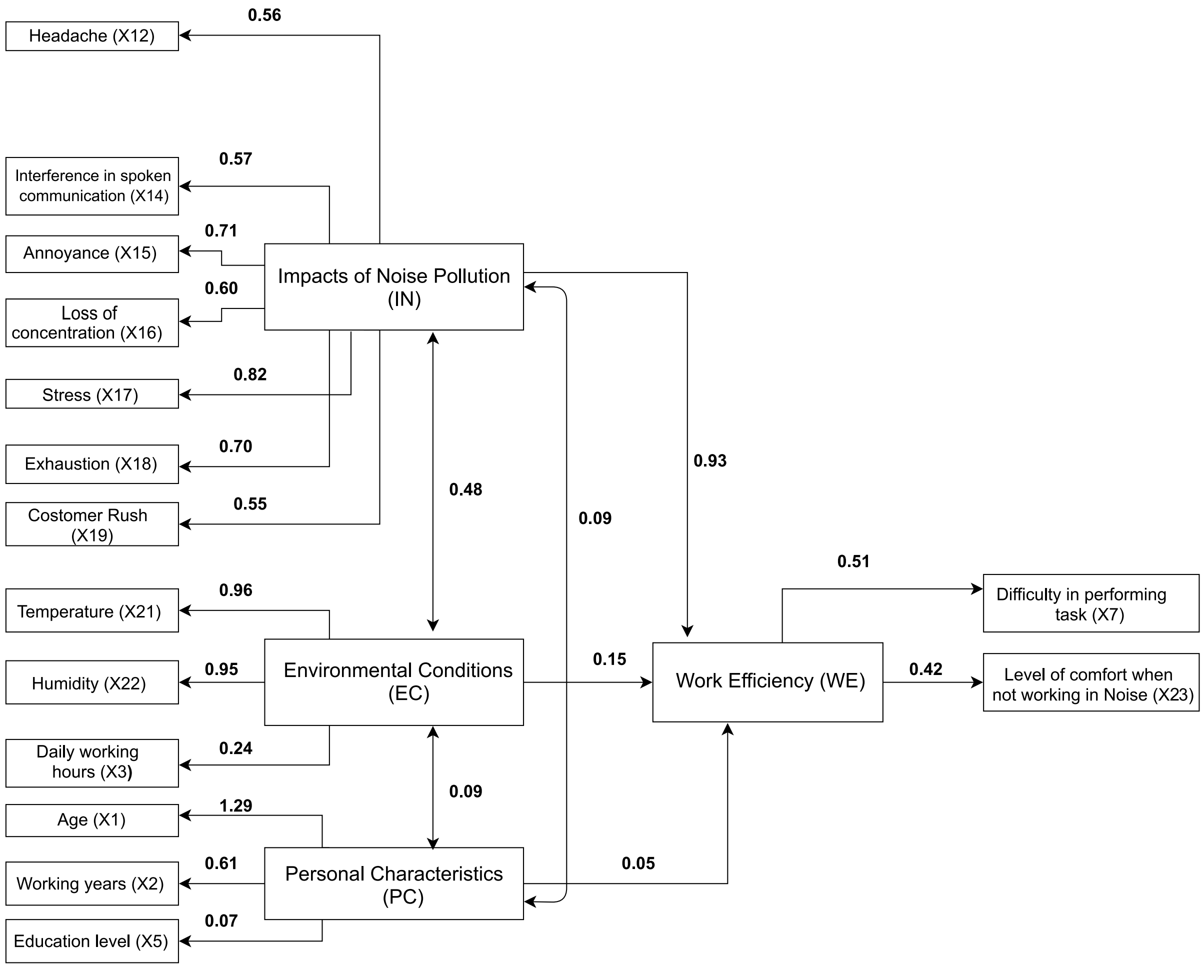

Fig. 4. Revised structural equation model with standardized estimates.

(X14)", which gives almost same concern. In one particular attempt, "interference with spoken communication (X14)" was omitted, and "hearing problem due to noise (X13)" was kept in analysis, but it gave bad goodness of fit. Another measured variable that was omitted in the revised model was "job satisfaction (X24)" because it gave a negative regression weight of −0.13 (Hair *et al.*, 2010). Statistically speaking the model is based on responses recorded from people working in the study area. The variable "job satisfaction (X24)" was removed because it showed contradiction (negative factor loading) as people in the study area although face noise pollution issues, still declared satisfaction with their job in the area. Hence, revised structural model given in Fig. 4 was considered as the final model as it satisfies most of the goodness of fit, as shown in Table 7, and it was used for drawing conclusions.

4.3.5. Path coefficients analysis

The path coefficients are nothing but the standardized form of linear regression weights, and they allow to discover probable causal relationships among statistic variables in the structural equation model (Stansfeld, Shipley, 2015). The idea of the "path coefficient" was initially given by (Golob, 2003), in which a specific diagram-based approached method was used to evaluate the relationships among the variables or factors in a multivariate structure. The investigation of path coefficients calculates the effects of variables in a causal system based on a structural equation, which is a mathematical equation giving the structure of the variables' relationships to each other (Hair *et al.*, 2010). In the current model, latent variables, namely "Impacts of noise pollution (IN)," "Environmental conditions (EC)," and "Personal characteristics (PC)" were related to "Work efficiency (WE)," as shown in Fig. 3. Table 8 gives the path coefficients of the four latent variables in the optimized SEM in descending order.

The potential variables that exerted a significant impact on work efficiency are discussed as follows.

a) Impacts of noise pollution showed a path coefficient of 0.971 and were found to have the most significant impact on Work efficiency. "Impacts of noise pollution" is a latent variable having noticeable adverse effects of noise pollution in human health like headaches due to noise pollution (X12), interference in spoken communication due

Table 7. The goodness of fit of the initial and revised structural equation model (original).

Type	Index	Fit standards of fitness	Obtained value (initial model)	Obtained value (revised model)	Result for the revised model
Absolute fit	Chi-square	As low as possible	743.8	420.8	Good Fit
	CMIN/DF	Between 2 to 5	6.502	5.010	Good fit
	RMR	< 0.05, good fit	0.066	0.059	Good fit
	RMSEA	< 0.08, not bad fit; < 0.05, good fit	0.089	0.076	Fit
	GFI	> 0.90, good fit	0.888	0.923	Good fit
Incremental fit	NFI	> 0.90, good fit	0.850	0.904	Good fit
	RFI	> 0.90, good fit	0.820	0.880	Close to fit
	IFI	> 0.90, good fit	0.870	0.921	Good fit
	TLI	> 0.90, good fit	0.843	0.901	Good fit
	CFI	> 0.90, good fit	0.870	0.921	Good fit
Parsimonious fit	PGFI	> 0.50, good fit	0.831	0.880	Good fit
	PNFI	> 0.50, good fit	0.707	0.723	Good fit
	PCFI	> 0.50, good fit	0.723	0.737	Good fit

Table 8. Path coefficients of the latent variables in the optimized structural equation model (original).

Relationships	Direct path coefficient
IN (Impacts of noise pollution) towards WE (Work efficiency)	0.931
EC (Environmental conditions) towards WE (Work efficiency)	0.153
PC (Personal characteristics) towards WE (Work efficiency)	0.050

to noise (X14), annoyance due to noise (X15), loss of concentration due to noise (X16), stress due to noise (X17), and feeling of exhaustion due to noise (X18). Therefore, these observed variables are having a predominant impact on the work efficiency of roadside shopkeepers. Additionally, the customer rush (X19) also impacts work efficiency.

b) Environmental conditions showed a path coefficient of 0.153 and were found to have an impact on Work efficiency. "Environmental conditions" is a latent variable that consists of two important parameters like ambient temperature and humidity and daily working hours in that condition. So, it is clear that ambient temperature and humidity have a significant impact on the work efficiency of roadside shopkeepers. This can also be explained as in the time of summer season when the temperature is high respondents face difficulty in working as compared to the winter season when the temperature is low.

c) Personal characteristics showed a path coefficient of 0.05 and were found to have minimal impact on work efficiency. "Personal characteristics" is a latent variable that consists of personal characteristics like age, working experience in the area, and education level. Hence, it can be concluded that age, experience and education level of respondents have a shallow effect on work efficiency as compared to another two latent variables namely "Impacts of noise pollution" and "Environmental conditions".

5. Conclusion

Integration of structural equation modelling and exploratory factor analysis was identified as a suitable method to study noise exposure effect on work performance efficiency. In the study, all possible variables affecting work efficiency in the influence of noise pollution found in the literature were considered for analysis. They comprise significant noise pollution effects, environmental conditions in which an individual works, and personal characteristics of the individual. Primarily, it was found that the work efficiency of open shutter shopkeepers is affected by significant noise pollution effects like headaches, stress, annoyance, interference in spoken communication, exhaustion, etc. It was also found that environmental conditions like temperature and humidity also have a slight effect on work efficiency. So, it can be said that in high-temperature conditions like in the summer season, work efficiency will be lower as compared to the efficiency in the winter season with lower temperatures. Lastly, it was observed that personal characteristics like age, working years and education has the least or negligible effect on work efficiency when working in traffic noise pollution. Here, the critical thing to notice is that the shopkeepers' daily work is not that much cognitive in nature, which explains why their efficiency is not affected by their personal characteristics. The statistical methods used for modelling are focused on assistive modelling to find out the most affecting parameters to affect performance efficiency under noise pollution. Since, from the revised SEM model, most affecting parameters are found, based on these parameters, prediction modelling is also possible to forecast work efficiency performance.

In developing countries like India, in the urban context, central business hubs exist, where the majority of shops are open shutter in nature. Also, traffic in those areas is heavy and heterogenic in nature (Banerjee *et al.*, 2008). This results in high noise pollution so people working in those areas are exposed to such noise for more than 12 hours daily. These conditions have been observed all over the world in developing countries like India (Banerjee, 2012). Following these facts, the present study is expected to be applicable for all the locations with similar traffic conditions, operational conditions and commercial or land use characteristics of the area. The methodology and results of the study shall work as reference and foundation for similar types of analysis to be performed at various locations with similar or slightly different features .

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