MULTIVARIATE ANALYSIS APPROACH TO IDENTIFY INFLUENCING FACTOR IN AN INDOOR ENVIRONMENT OF DYEING AND PRINTING UNIT: AN INDIAN PERSPECTIVE

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Abstract

The indoor environment comprises air quality and working conditions. Indoor work environmental condition is significant as they affect the comfort, health, and performance of occupants. Industrial indoor environments differ from residential ones due to the adoption of manufacturing processes and the use of a variety of raw materials. Workplace environmental condition is assessed by evaluating various comfort and pollution parameters. This study was carried out in the textile dyeing and printing industry. In this study, fifteen parameters were considered to evaluate work environmental conditions in the industry. The stenter machine area and printing machine area were two locations selected based on the manufacturing process. Continuous monitoring had been carried out at the selected locations for 5 days in the winter, summer and monsoon seasons. Data on the selected parameters were recorded at minute intervals. Principal component analysis was performed to determine the parameters that significantly affect the indoor work environment. The results obtained show that the WBGT index at every place was higher than the prescribed norms. The average concentration of particulate matter, nitrogen dioxide and ozone was also observed higher. Principal component analysis at both locations indicated thermal comfort factors dominated the indoor work environment, followed by particulate matter, nitrogen dioxide, ozone, and a total volatile organic compound. The analysis revealed that water, high temperature, and chemicals were the major sources of indoor air pollution.

Keywords: Comfort parameters, Indoor work environment, Principal component analysis, Textile dyeing and printing, Thermal comfort, WBGT index

1. Introduction

The Lancet Commission report on Pollution and Health stated that air pollution is one of the significant causes of death. One in every six people worldwide died due to air pollution. The breathing of polluted air causes around 6.5 million deaths annually. Out of these, 3.2 million fatalities were attributed to indoor air pollution (Fuller et al., 2022). Air pollution demands immediate attention as it has an adverse effect on the quality of life and living standards. In the outdoor environment, a large volume of air and enough air velocity exist, which can quickly disperse the pollutants. In contrast, indoor air pollution is a dynamic and intricate phenomenon because it depends on the types of processes and activities conducted in an enclosed space (Wei et al., 2016). In the indoor environment, due to less space, a limited volume of air and less air velocity is available, which results in poor dispersion of pollutants. Hence, indoor air pollution adversely affects the health and comfort of people (Ghorani-Azam et al., 2016)**.** Over the last few decades, India has witnessed tremendous growth in industrialization and urbanisation. This leads to an increase in office buildings, commercial complexes, industrial buildings, vehicular growth, and population density. These factors are responsible for the deterioration of both indoor and outdoor air quality. Countries near the equator noticed a substantial variation in humidity and temperature, resulting in issues associated with an increase in temperature, humidity, and other indoor environmental factors. Indoor air quality (IAQ) can be challenging to forecast since it incorporates meteorological parameters as well as pollutants generated due to the activities performed within the premises. A good IAQ is required for an efficient and healthy environment. IAQ also has an impact on the performance, productivity, and efficiency of workers (Mata et al., 2022). Poor IAQ can increase short- and long-term health concerns such as respiratory diseases, bronchitis, pneumonia, sinusitis, eye irritation, and allergic reactions. Identifying significant causes of indoor air pollution is essential for developing strategies for reducing it. Because indoor air pollution is influenced by a variety of factors, it is critical to investigate their interdependence and mutual consequences. (Lin et al., 2007) suggested that sometimes a univariate analysis approach might yield unreliable and inaccurate results. Therefore, multivariate analysis approaches such as factor analysis (FA), multivariate linear regression (MLR), principal component analysis (PCA), and agglomerative hierarchical cluster analysis can be applied to investigate correlations among various parameters. From these PCA is a commonly employed multivariate statistical technique for identifying significant parameters and potential pollution sources by extracting principal components (Li et al., 2020). Although its wide use, PCA had been used very limitedly for industrial research work about indoor air pollution. Research carried out worldwide to evaluate IAQ using PCA in residential, industrial, and public places is summarised below.

Taneja et al. (2008) adopted the PCA to analyse data and recognise significant factors contributing to indoor air quality (IAQ) in residences in the urban region of Agra City, India. The finding of the study revealed that combustion activities and the use of oil were the most prevalent sources of indoor air pollution. Based on sick building complaints, Syazwan et al. (2012) performed PCA to identify indoor air pollutants that impaired health in nonindustrial workplaces. The most common factors reported by the most complaining group were fungus; indoor chemical dispersion; detergent; refurbishment; thermal comfort; fresh air intake; and ventilation. Khanum et al. (2021) employed PCA to categorise PM_{10} sources in the urban region of Lahore. The sources were classified into three distinct categories, including road dust and vehicular sources, industrial sources and steel industry, and combustion process. PCA was successfully used to identify potential sources of heavy metal contamination in the indoor environment of residences situated in regions with high traffic, low traffic, and rural settings in Neyshabur, Iran. They identified major sources of heavy metal pollution, were traffic, latex paints, abrasion of rubber and alloys, corrosion of vehicle parts, urban road construction, and indoor smoking (Naimabadi et al., 2021).

PCA was performed to determine factors impacting IAQ in photocopying shops and discovered that the toner and heating of copier machines were the leading sources of emission and responsible for pollution in photocopying shops (Kiurski et al., 2016; Morlini, 2007; Pérez-Arribas et al., 2017). Samsuri Abdullah (2018) utilised PCA to investigate IAQ in the refinery industry in Malaysia. The results showed that chemical pollutants, ventilation, and thermal comfort play a vital role in impacting IAQ. Furthermore, through the implementation of PCA, various investigations have discerned that sources of metal pollution in diverse indoor settings include coal combustion, automobile emissions, agricultural activities, metallurgical operations, mining activities, printing inks, paints, electroplating processes, and building materials. (Bai et al., 2020; Iwegbue et al., 2020).

Kim et al. (2010) utilized the PCA approach to evaluate and identify the sources, responsible for pollution in the subway station in Korea. These features might therefore be utilised to improve the handling of substantial fluctuations in the air quality in tube systems, allowing significant changes in IAQ to be noticed promptly. Two monitoring models had been developed to study climate change. Darus et al. (2012) performed a PCA to identify the underlying factors that influence the concentration of metals in the indoor environment of nursery school buildings. The study also aimed to ascertain the sources of these metals. Khatun (2009) employed PCA to assess the extent of environmental degradation across 51 countries. The study utilised six variables, namely total fertility rate, fuel consumption, GDP per capita, water supply, sanitation, and electricity. The study findings indicate that the factors contributing to environmental degradation comprise GDP per capita, fuel consumption, water supply, and electricity. Eman and Ghada successfully predicted the air quality index by using PCA combined with an artificial neural network (Sarwat & I El-Shanshoury, 2018). Some authors have successfully employed PCA in conducting source apportionment studies concerning air pollutants, particulate matter, and heavy metal pollution in the urban environment (Onat et al., 2012; Shiva Nagendra & Khare, 2003; Widiana et al., 2017).

The objective of the present study is to reveal the impact of industrial processes on indoor air quality by extracting principal components. The PCA was utilized in this study to (1) explore the relationship with various pollutants in an indoor environment and (2) identify the main contributions of pollution sources governing indoor air quality. The absence of IAQ guidelines in India, as noted by (Goyal & Khare, 2012), the findings of this study will be also helpful in developing IAQ guidelines for particular industries in the future.

2. Material And Methodology

Study area

Evaluation of IAQ was performed at a dyeing and printing processing house located in an industrial estate in Surat, Gujarat, India, which is the main hub for the production of fabrics in India. More than 400 dyeing and printing processing houses are situated in diverse industrial estate clusters surrounding Surat City. Dyeing and printing is a batch process that depends on the quality of raw fabrics, customer requirements, and the design to be printed on the fabrics. In a processing house, the raw fabric obtained from weaving commonly known as the 'grey cloth', is transformed into final finished products such as sarees, bedsheets, and other fabric products through wet processing technology. The wet processing technique comprises different stages, namely sizing, desizing, scouring, bleaching, mercerizing, dyeing, printing, and finishing. Fig. 1 shows the general process diagram followed in the industry.

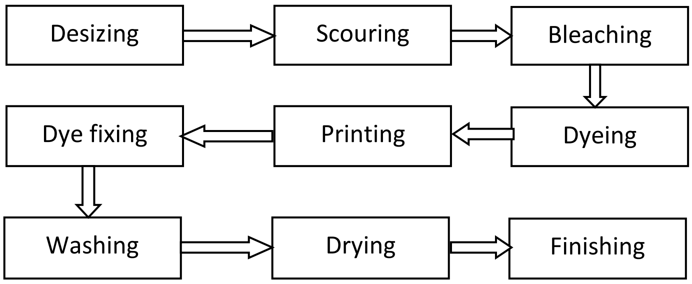


Figure 1 Process flow diagram of a dyeing and printing house.

All the aforementioned operations are performed at temperatures ranging from 100°C to 180°C inside the heating and drying chamber of process equipment. Each of above mention processes uses a significant amount of water, along with a variety of chemicals, dyes, solvents and other substances, which are responsible for the generation of pollutants. Large fluctuations in both the humidity and temperature have been observed across the plant. Five basic operations were carried out on the raw fabric to produce the final finished product and were identified. Table 1 represents the temperature ranges in different processes, chemicals used and the pollutants that are emitted as a result of these activities (Sharma, 2015). The process carried out in the stenter machine (SM) and printing machine (PM) is the main heart of the overall process. These two areas were considered to determine the IAQ of the industry as a whole.

Table 1 Process and temperature settings in the textile processing house

Type of machine	Process	Temperatures	Chemicals used	Air Emission
Jet dyeing machine	Desizing and scouring	130°C –150°C	NaOH and Enzyme	VOCs and formaldehyde
Stenter machine	Set the width of the printed fabric, final heat setting, and crease removal	150°C –180°C	Dispersing agent, dyes, and auxiliaries	VOCs, combustion gases, and particulate matter
Looping machine	Heat setting of dyes	130°C –160°C		Volatilisation of dyes, chemicals applied during printing
Printing machine	Printing	130°C –150°C	Dyes and adhesives	VOCs, formaldehyde, combustion gases, and particulate matter
Washing Basin	Removal of excess dyes	110°C –120°C	NaOH, Auxiliaries	VOCs, formaldehyde, combustion gases, and particulate matter

Study parameters

To determine IAQ, a large amount of data is required about various meteorological and pollution parameters. In this study, IAQ in industries was determined with respect to thermal comfort, particulate matters and some gaseous pollutants. Thermal comfort parameters considered for the study are dry bulb temperature (DBT, °C), globe temperature (GT, °C), natural web bulb temperature (NBT, °C), wind speed (WS, m/s), and relative humidity (RH, %). From the obtained data thermal comfort indices known as wet bulb globe temperature (WBGT) index was calculated using equation 1.

$$WBGTindoor = 0.7NBT + 0.3GT \text{ ....} \qquad \text{Eq (1)}$$

Particulate matter concentration was measured in PM_{10} (μg/m^3) and $PM_{2.5}$ (μg/m^3). Gaseous pollutants considered in the study were carbon dioxide (CO_2), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), the total volatile organic compound (TVOC) and formaldehyde (HCHO). All the gaseous pollutants were measured in ppm. Since India does not have any standards for IAQ, the guidelines of various countries and agencies were studied to evaluate IAQ. Most of the countries considered the reference value as an 8-hour average value of the pollutants. As far as possible threshold limiting value (TLV) suggested by USEPA, OSHA, NIOSH, ASHRAE and ACGIH were taken into consideration. So, in the present study, an 8-hour average value is considered for further analysis. The maximum allowable permissible limiting values of each pollutant selected in the study are summarized in Table 2 (Ahmed Abdul–Wahab et al. 2015; American Conference of Governmental Industrial Hygienist 2005; American Society of Heating and Air-Conditioning Engineers (ASHRAE) 2004).

Table 2 Threshold limiting value of study parameters

Variables	Threshold limiting value	Organization
$PM_{2.5}$	65 μg/m^3	US EPA
PM_{10}	150 μg/m^3	US EPA
CO_2	5000 ppm	OSHA
SO_2	2 ppm	ACGIH, NIOSH
NO_2	5 ppm	OSHA
CO	50 ppm	US EPA
O_3	0.1 ppm	US EPA
TVOC	3 ppm	DOSH
HCHO	0.75 ppm	US EPA
Wind Speed	0.25 m/s	WHO
WBGT Index	28 ^{o}C	ACGIH
NBT	29 ^{o}C	Indian Factory Act
DBT	22.5 - 26 ^{o}C (summer)	ASHRAE
RH	30 - 70	ASHRAE

3. Methodology

In this study, from the available multivariate techniques, PCA was used as the main tool. To obtain the desired output, a large data set is required to convert it into less-dimensional data, at the same time variability between the variable were kept intact. Large data sets correlating with each other were converted into a compact number of non-correlated and orthogonal variables, as reported (Polanco Martínez, 2016). The loading plot was used to visualize the weightage of variables and identify variables exerting the most substantial effect on principal components (PCs). The methodology adopted in this study is shown in Fig.2.

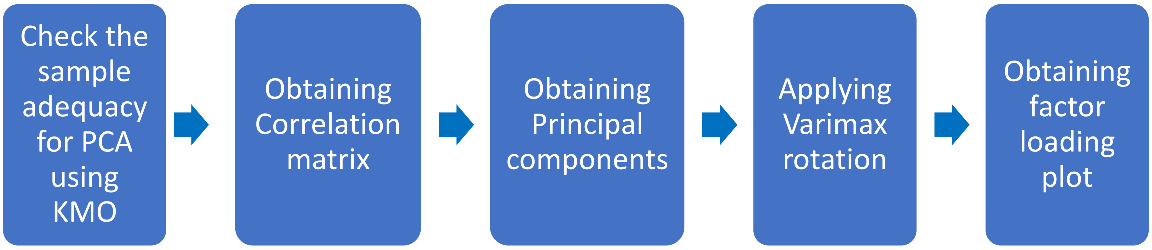


Figure 2 Methodology adopted for PCA

Before performing PCA, the sample adequacy is evaluated using Kaiser-Meyer-Olkin (KMO) and Bartlett's test. If KMO is larger than 0.5, this signifies that monitoring data were sufficient for PCA. Alternatively, Bartlett's test revealed that some variables were significantly ($p>0.001$) interrelated to one another and hence acceptable for factor analysis (Awang et al., 2015). Pearson's correlation was calculated to determine the correlation among variables. These findings could indicate a positive (0 to 1) or negative (0 to −1) relationship between the two variables. Correlation coefficient values of >0.9, between 0.68 and 0.9, between 0.36 and 0.67, and <0.36 indicated very strong, strong, moderate, and weak correlation, respectively, between the two variables (Sun et al., 2021). A significance level for correlation was set at 0.05. To obtain the principal component (PC), a correlation matrix was used. According to the Kaiser criterion, the principal component with an eigenvalue higher than or equal to one is deemed statistically significant (Abdul-Wahab et al., 2005). The eigenvalue obtained in the analysis was finally considered to choose PC. The PC for which the eigenvalue obtained was >1, is considered a PC.
A varimax rotational factor analysis was performed to determine the main factors contributing to the levels of pollution. A set of many intercorrelated variables is replaced by orthogonal transformations in varimax rotation by a small number of linearly independent variables (Masih & Taneja, 2006). The adjustment, or rotation, aims to optimize the variation shared among variables. When shared variance is maximised, the results more discretely reveal how data correlate with each PC. To maximise variance, the squared correlation of items related to one factor is increased, whereas the correlation with any other component is reduced. The correlation between variables and factors is represented by factor loadings generated after varimax rotation (Dominick et al., 2012; Taneja et al., 2008). The greater a variable's loading, the more that factor participates in the variation explained by the specific principal component. Loadings with absolute values larger than 0.5 or 50% are usually preferred for the principal component interpretation.

4. Data Collection

The QuesTemp36 area heat stress monitor was used to collect data regarding NBT, DBT, GT, and RH. Parnaair passive sampler was used to collect the data on gaseous pollutants and particulate matter. Kusam Meco KM 732 hot wire anemometer was used to collect the observation of air velocity. Data on every selected parameter were recorded at an interval of one minute. Instruments were placed at a height of 1.2–1.5 m, which is the average height above the abdominal level in humans, to collect data. Observations were recorded at each location for three seasons namely monsoon, winter and summer. Continuous monitoring was performed for 12 hours (8 AM to 8 PM) for continuous 5 days at each location in each season. 3600 observations were collected in each season. PCA was performed using the XLSTAT-2022 add-in. Table 3 summarizes the descriptive statistics of measured data.

Table 3 Descriptive statistics of study parameters

Variables	Statistics	SM			PM		
		Monsoon	Winter	Summer	Monsoon	Winter	Summer
NBT (°C)	Min	24.2	17.6	27.7	29.1	19.6	29.7
	Max	25.8	25.7	36.3	33.9	28.0	32.2
	Mean	25.1	22.2	31.6	32.2	24.8	31.0
	Std dev	0.4	1.8	2.0	0.7	1.4	0.7
DBT (°C)	Min	28.1	21.6	36.1	35.2	26.0	38.6
	Max	45.4	37.2	48.5	48.8	41.0	44.5
	Mean	37.8	32.1	43.7	43.2	35.1	41.8
	Std dev	4.5	3.5	2.4	3.9	3.2	1.6
GT (°C)	Min	37.1	22.3	38.1	41.5	26.4	42.5
	Max	44.4	37.6	48.4	49.0	41.6	46.2
	Mean	41.0	32.7	42.8	46.3	35.4	44.5
	Std dev	1.8	3.4	2.6	1.1	3.4	1.0
WBGT (°C)	Min	28.2	19.1	31.5	32.8	21.7	33.5
	Max	45.3	28.9	38.7	44.3	32.0	36.4
	Mean	32.3	25.3	35.0	37.7	28.0	35.1
	Std dev	5.2	2.3	1.3	2.6	2.0	0.8
Humidity (%)	Min	44.6	33.5	33.8	33.2	34.7	44.9
	Max	69.9	61.1	71.1	63.3	52.6	70.1
	Mean	53.2	43.5	54.8	43.7	43.3	61.0
	Std dev	5.3	5.2	10.0	3.7	4.7	6.0
$PM_{2.5}$ ($\mu g/m^3$)	Min	27.0	59.0	57.0	31.0	47.0	21.8
	Max	1000.0	1000.0	1000.0	1000.0	1000.0	558.2
	Mean	188.1	193.4	618.8	268.0	208.8	143.3
	Std dev	165.2	173.5	262.9	248.8	130.6	73.5
PM_{10} ($\mu g/m^3$)	Min	30.0	66.0	64.8	35.0	53.0	24.6
	Max	1000.0	1000.0	1000.0	1000.0	1000.0	651.7
	Mean	215.5	222.3	675.6	299.3	244.7	166.5
	Std dev	187.4	188.2	260.4	262.7	160.3	86.2
CO_2 (ppm)	Min	404.0	416.0	133.3	379.0	410.0	400.0
	Max	668.0	2056.0	809.0	978.0	4009.0	2304.8
	Mean	447.5	505.0	339.6	556.6	490.1	510.5
	Std dev	32.8	87.1	111.4	139.0	164.4	99.2
SO_2	Min	0.00	0.00	0.00	0.00	0.00	0.00

(ppm)	Max	27.75	18.89	0.03	31.69	0.56	30.55
	Mean	0.26	0.22	0.00	1.01	0.01	0.96
	Std dev	1.52	0.70	0.00	3.40	0.06	2.93
NO_2 (ppm)	Min	1.50	0.99	1.46	1.51	1.24	1.38
	Max	27.19	28.24	27.21	26.97	1.46	27.15
	Mean	2.13	1.36	22.23	16.41	1.34	2.03
	Std dev	0.86	0.90	5.01	11.54	0.03	2.48
CO (ppm)	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	4.38	3.76	0.51	30.32	0.91	14.38
	Mean	0.14	0.18	0.00	0.31	0.02	0.03
	Std dev	0.41	0.46	0.01	1.42	0.11	0.36
O_3 (ppm)	Min	0.00	0.07	0.06	0.00	0.05	0.00
	Max	0.42	1.46	22.03	21.56	0.17	3.03
	Mean	0.08	0.14	17.39	12.14	0.12	0.91
	Std dev	0.03	0.05	4.58	10.10	0.02	0.67
TVOC (ppm)	Min	0.01	0.01	0.00	0.01	0.00	0.01
	Max	7.31	14.95	5.10	13.60	12.98	13.46
	Mean	0.43	0.82	1.84	1.07	1.34	5.67
	Std dev	0.64	1.52	1.25	2.11	2.34	3.48
HCHO (ppm)	Min	0.00	0.00	0.00	0.01	0.01	0.00
	Max	2.06	0.90	1.25	5.00	5.00	5.00
	Mean	0.18	0.15	0.62	0.80	0.06	0.40
	Std dev	0.18	0.19	0.36	0.95	0.32	0.83
WS (m/s)	Min	0.00	0.00	0.00	0.00	0.00	0.00
	Max	1.75	1.10	1.25	1.15	1.80	2.25
	Mean	0.71	0.24	0.56	0.55	0.50	0.95
	Std dev	0.35	0.26	0.33	0.33	0.40	0.57

5. Result And Discussion

The descriptive statistic shows that except winter season at both locations, the WBGT index was found higher than the TLV suggested by the standard. Due to higher the ambient temperature in the summer and monsoon seasons, heat convection is not possible, which results in a higher WBGT index. Also, the DBT in the manufacturing area was found to be higher than the prescribed limit. Both particulate matter concentrations in terms of $PM_{2.5}$ and PM_{10}, were observed greater than the standard value of 65 µg/m^3 and 150 µg/m^3. Ozone concentration in all seasons was found much higher than the limit of 0.1 ppm, which also indicates the amount of high temperature, NO_2, and TVOC in the indoor environment. Descriptive analysis shows the thermal comfort variable, particulate matter, and organic pollutants have more influence on IAQ.

Pearson's correlation analysis

Using monitoring observation, correlation analysis was performed. Tables 4 & 5 represent the correlation matrix at the stenter machine area and printing machine area respectively.

Table 4 Correlation analysis at stenter machine area

Variable	$PM_{2.5}$	PM_{10}	CO_2	SO_2	NO_2	CO	O_3	TVOC	HCHO	WS	WBGT Index	GT	NBT	DBT	RH
$PM_{2.5}$	1														
PM_{10}	0.996	1													
CO_2	-0.348	-0.353	1												
SO_2	-0.078	-0.077	0.162	1											
NO_2	0.642	0.652	-0.757	-0.122	1										
CO	-0.094	-0.089	0.273	0.187	-0.223	1									
O_3	0.635	0.644	-0.757	-0.138	0.998	-0.221	1								
TVOC	0.171	0.174	0.085	0.046	0.145	-0.005	0.150	1							
HCHO	0.378	0.382	-0.253	-0.064	0.466	-0.055	0.463	0.195	1						
WS	0.097	0.101	-0.172	-0.031	0.121	0.032	0.106	-0.093	0.085	1					
WBGT Index	0.463	0.471	-0.606	-0.164	0.590	-0.243	0.572	-0.047	0.216	0.268	1				
GT	0.469	0.472	-0.573	-0.177	0.533	-0.266	0.506	-0.069	0.207	0.338	0.851	1			
NBT	0.620	0.629	-0.745	-0.180	0.873	-0.262	0.862	0.056	0.404	0.210	0.801	0.771	1		
DBT	0.514	0.515	-0.613	-0.168	0.662	-0.262	0.641	0.006	0.315	0.250	0.589	0.858	0.801	1	
RH	0.193	0.208	-0.456	-0.021	0.430	0.080	0.424	-0.121	0.228	0.399	0.433	0.299	0.517	0.244	1

A stenter machine is used to dry fabrics completely and set out the required width of the fabric before the printing operation, also after the printing operation excessive dyes should be thoroughly washed and the fabric require to be softened was carried out in this process. Thermopack is used to generate the required heat, which will be heated oil and this oil is circulated in the stenter machine to maintain the required temperature. The temperature used in this process generally ranges from 110°C to 180°C depending on the quality of the fabric. This is completely a heat-dominating process. Correlation analysis shows that $PM_{2.5}$ and PM_{10} show moderate correlation with NO_2, O_3, NBT, GT, DBT, and WBGT index, while with other variables they show weak or negative correlation. CO_2, SO_2, and CO show positive weak correlations with each other, whereas with other variables it shows negative correlations. NO_2 and O_3 show a very strong correlation with each other, with NBT it reflects a strong correlation, with particulate matter, WBGT index, GT, and DBT it shows moderate correlations. Whereas with SO_2, CO, and CO_2 it has a negative correlation. Formaldehyde shows moderate to weak correlations with variables except for SO_2, CO, and CO_2. WBGT index, GT, NBT, and DBT show a strong correlation with each other, while it reflects a moderate correlation with particulate matter, NO_2, and O_3. RH shows a weak correlation with variables except for SO_2 and CO_2. With CO, it is having very weak correlation.

Table 5 Correlation analysis at printing machine area

Variable	$PM_{2.5}$	PM_{10}	CO_2	SO_2	NO_2	CO	O_3	TVOC	HCHO	WS	WBGT Index	GT	NBT	DBT	RH
$PM_{2.5}$	1														
PM_{10}	0.995	1													
CO_2	0.211	0.207	1												
SO_2	-0.102	-0.107	0.050	1											
NO_2	0.404	0.383	0.346	0.191	1										

CO	0.023	0.024	0.048	0.316	0.105	1									
O_3	0.443	0.423	0.342	-0.086	0.931	-0.014	1								
TVOC	-0.173	-0.178	-0.023	0.126	-0.171	-0.037	-0.194	1							
HCHO	0.057	0.044	0.037	0.144	0.266	0.026	0.204	-0.034	1						
WS	-0.097	-0.096	-0.044	0.029	-0.073	-0.029	-0.085	0.185	-0.002	1					
WBGT Index	-0.025	-0.056	0.154	0.099	0.520	0.051	0.524	0.081	0.252	0.090	1				
GT	-0.110	-0.141	0.053	0.135	0.403	0.069	0.392	0.147	0.251	0.113	0.944	1			
NBT	-0.088	-0.118	0.061	0.135	0.415	0.070	0.406	0.154	0.263	0.127	0.948	0.988	1		
DBT	-0.146	-0.172	-0.042	0.104	0.270	0.073	0.270	0.126	0.227	0.089	0.799	0.943	0.927	1	
RH	-0.200	-0.200	-0.075	0.261	-0.210	-0.004	-0.316	0.515	0.025	0.310	0.061	0.112	0.149	0.012	1

Printing is the process of applying dyes in such a way that the required impression is printed on the fabric with the help of screens. In this process, various types of dyes depending on printing quality are used. Dyes were prepared by mixing them in the gum. Some types of adhesives are used so that dyes stick to the fabrics. After printing prints on the fabrics, they are dried so that the dyes do not fade and spread. The correlation coefficient matrix shows, the particulate matter has a moderate correlation with NO_2 and O_3, while with other variables it seems very weak to negative correlation. CO_2, SO_2, and CO show a very weak to negative correlation with all the variables. TVOC shows a moderate correlation with RH, seen that RH is responsible for variation in the TVOC concentration. Thermal comfort variables, WBGT index, GT, NBT, and DBT show a strong correlation with each other, while it has a moderate correlation with NO_2 and O_3, directed that temperature is responsible for the generation of these both pollutants.

Principal component analysis

PCA was performed using the correlation matrix. Fifteen eigenvalues were obtained for fifteen PCs. Tables 6 and 7 present the variability exhibited by each PC as well as the cumulative variability for the stenter machine area and printing machine area, respectively. Fig. 3 represents the scree plot showing the eigenvalues, variability, and cumulative variability of the stenter machine area and printing area. In PCA, factors having an eigenvalue >1 are only considered significant and included in further analysis.

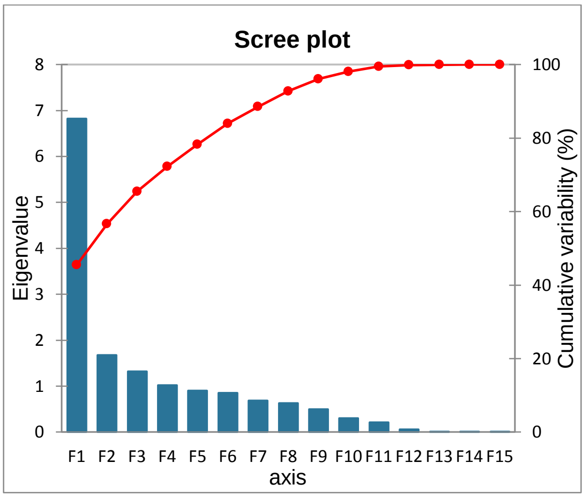
Table 6 Eigenvalue of each principal component at the stenter machine area.

Variable	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
Eigenvalue	*6.822*	*1.675*	*1.324*	*1.019*	0.903	0.851	0.688	0.630	0.498	0.303	0.210	0.058	0.014	0.004	0.001
Variability	*45.48*	*11.17*	*8.82*	*6.79*	6.02	5.67	4.59	4.198	3.321	2.017	1.402	0.389	0.091	0.024	0.009
Comm. variability	*45.48*	*56.65*	*65.47*	*72.27*	78.29	83.96	88.55	92.75	96.07	98.07	99.49	99.88	99.97	99.99	100

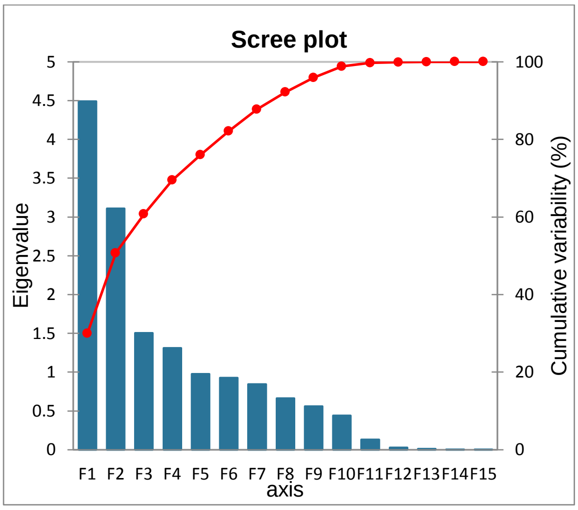
As shown in Table 6, for the stenter machine area first 4 PCs show an eigenvalue greater than 1, presenting cumulative variability of 72.27%. So, for further analysis, the first 4 PCs for both study locations were considered.

Table 7 Eigenvalue of each principal component at the printing machine area.

Variable	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
Eigenvalue	*4.494*	*3.111*	*1.506*	*1.310*	0.976	0.926	0.843	0.661	0.559	0.439	0.132	0.027	0.011	0.005	0.001
Variability	*29.96*	*20.74*	*10.04*	*8.73*	6.51	6.17	5.62	4.41	3.72	2.93	0.88	0.18	0.07	0.03	0.01
Comm. variability	*29.96*	*50.70*	*60.70*	*69.47*	75.98	82.15	87.77	92.18	95.90	98.83	99.71	99.89	99.96	99.99	100



3(a) Scree plot at the stenter machine area



3(b) Scree plot at printing machine area

Figure 3 Scree plot of eigenvalue, variability, and cumulative variability at different locations

For the printing machine area, from Table 7, the first 4 PCs having eigenvalue greater than 1, shows a cumulative variability of 69.47%. After the extractions of PCs, varimax rotation was applied. The result obtained for factor loadings and correlation between factors and variables for the stenter machine area is presented in Table 8. Fig. 4 shows the factor-loading plot and Fig.5 reflects the significant parameters influencing each PC for the stenter machine area.

Table 8 Correlation between factors and variables at stenter machine area

Variable	D1	D2	D3	D4
$PM_{2.5}$	0.282	-0.058	0.014	*0.904*
PM_{10}	0.295	-0.053	0.021	*0.901*
CO_2	*-0.750*	-0.259	0.376	-0.143
SO_2	-0.045	-0.027	*0.530*	-0.015
NO_2	*0.822*	-0.001	-0.203	0.456
CO	-0.092	0.092	*0.761*	-0.039
O_3	*0.828*	-0.025	-0.205	0.439
TVOC	0.113	*-0.546*	0.145	0.282
HCHO	*0.566*	-0.219	0.123	0.280
Wind Velocity	0.099	*0.704*	0.227	0.150
WBGT Index	0.415	*0.489*	-0.345	0.463
GT	0.265	0.553	-0.427	*0.569*
NBT	*0.700*	0.270	-0.310	0.518
DBT	0.394	0.331	-0.404	*0.566*
RH	*0.677*	0.494	0.246	-0.042

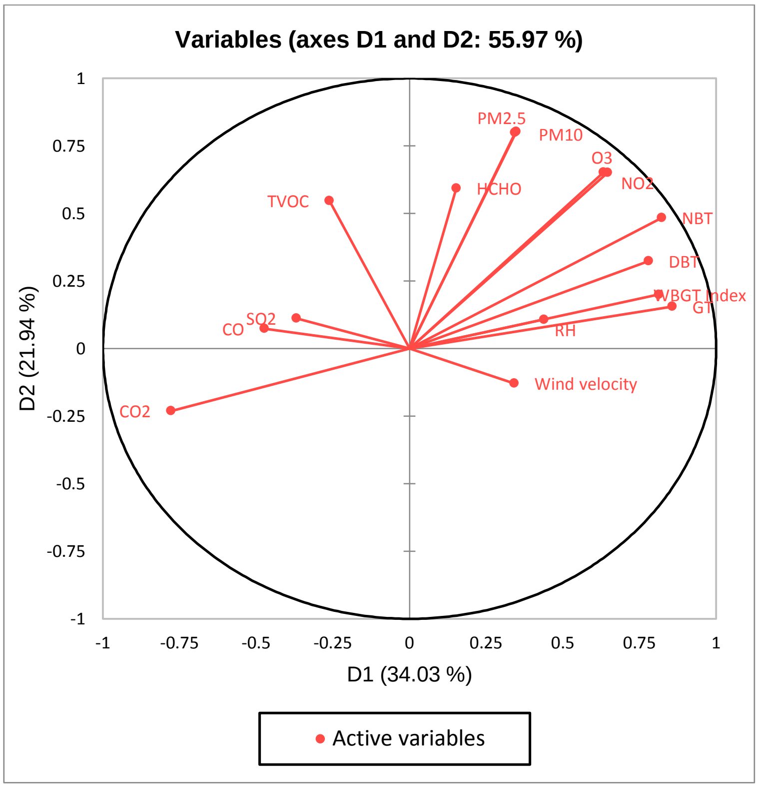


Figure 4 PCA loading plot after varimax rotation at stenter machine area

PCA analysis was performed on the correlation matrix, which extracts 15 PCs shown in Table 3. From these 15 PCs, the first 4 PCs having eigenvalue greater than 1 were taken into consideration, showing total variability of 72.27%. Factor loading obtain after varimax rotation was presented in Table 7. The higher the factor loading more is the contribution of that factor in the PCs. Factor loading of more than 0.5 is considered as the significant factor in the contribution that PCs represent in Figure 5.

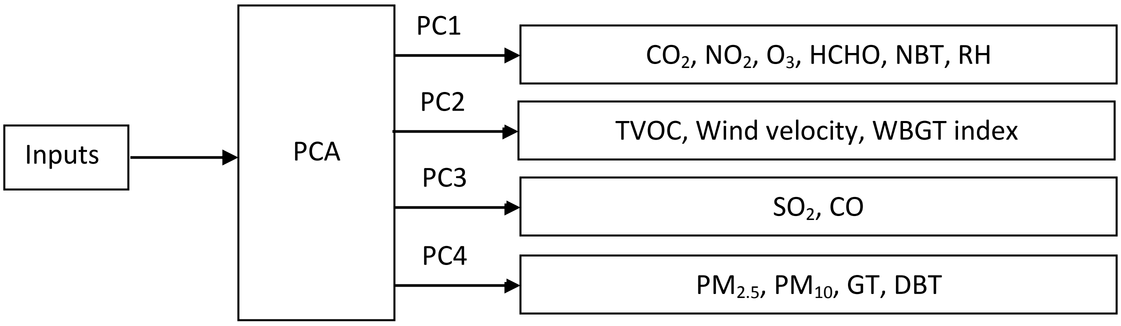


Figure 5 Principal components for IAQ at stenter machine area

Factor loading showed that PC1 had a strong loading of CO_2, NO_2, O_3, HCHO, NBT and RH. It reflects that the temperature-related variables are dominating in this process and also contributing highly to the IAQ. In PC2 variables that contribute to this PC are TVOC, Wind velocity and WBGT index. PC3 shows the high factor loading of CO and SO_2. PC4 reflects the higher factor loading of $PM_{2.5}$, PM_{10}, GT and DBT. The process carried out in this is strengthening the fabric and setting the required width of the cloth, which generates micro fibre and contributes to the particulate matter concentration. Also, micromolecules of gaseous pollutants are contributing to the particulate matter concentration. The results of factor loading revealed that higher WBGT index, DBT, GT, and NBT were observed due to high temperature in the process. High temperature is responsible for the volatilisation of dyes, adhesives, and other chemicals, resulting in concentration of TVOC, HCHO, NO_2 and O_3.

The result obtained after the varimax rotation on factor loadings and the correlation between factors and variables for the printing machine area is presented in Table 9. Fig. 5 shows the factor-loading plot and Fig.6 reflects the significant parameters influencing each PC for the printing machine area.

Table 9 Correlation between factors and variables at printing machine area

Variable	D1	D2	D3	D4
$PM_{2.5}$	-0.137	*0.910*	-0.044	-0.104
PM_{10}	-0.169	*0.904*	-0.044	-0.105
CO_2	0.074	0.452	-0.028	0.169
SO_2	0.076	-0.017	0.197	*0.818*
NO_2	0.500	*0.668*	-0.232	0.209
CO	0.014	0.023	-0.109	*0.741*
O_3	0.508	*0.682*	-0.293	-0.050
TVOC	0.073	-0.107	*0.757*	0.029
HCHO	0.312	0.140	-0.033	0.235
Wind Velocity	0.086	-0.010	*0.585*	-0.115
WBGT Index	*0.949*	0.116	0.059	0.030
GT	*0.977*	-0.018	0.116	0.042
NBT	*0.972*	0.011	0.146	0.045
DBT	*0.916*	-0.124	0.052	0.007
RH	0.006	-0.141	*0.830*	0.179

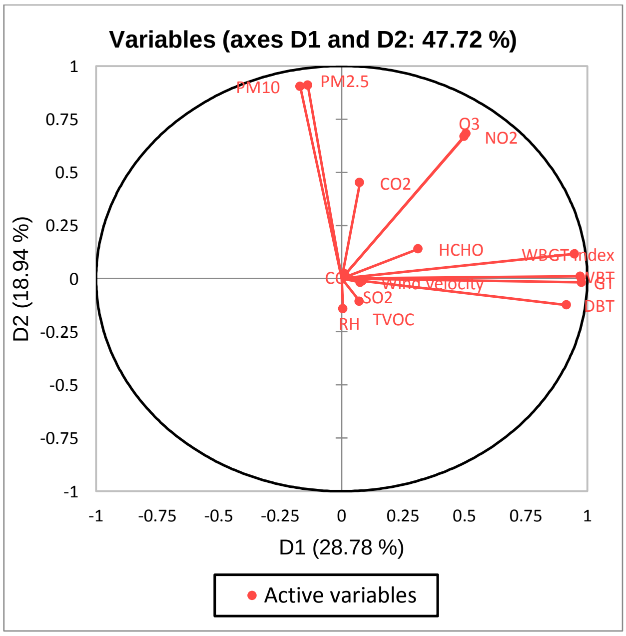


Fig 5 PCA loading plot after varimax rotation at printing machine area

PCA results showed that the first 4 PCs showed an eigenvalue of >1; thus, these components were found to be significant. The four PCs exhibited a variance of 29.96%, 20.74%, 10.04% and 8.73% respectively, reflecting a total variance of 69.47% shown in Table 6. Factor loading after varimax rotation is present in Table 8. Figure 6 shows the significance of factors with each PC.

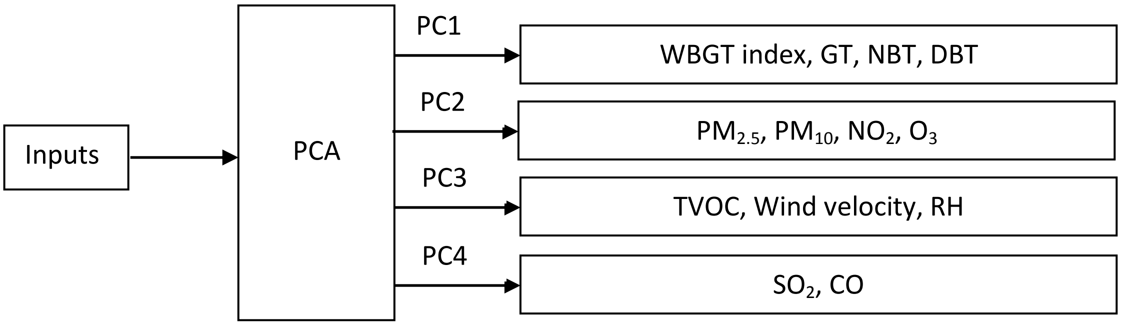


Figure 6 Principal components for IAQ in the printing machine area

Factor loading obtained after varimax rotation indicated that the first PC shows the higher contribution of WBGT index, GT, NBT and DBT. This conveys that the thermal comfort variables are more significant to PC1. PC2 determine the significant variables including $PM_{2.5}$, PM_{10}, NO_2 and O_3. This shows the particulate matter dominating these PCs. PC3 and PC4 reflect the higher factor loading of TVOC, wind velocity, RH and SO_2, and CO respectively. The results of factor loading indicated that only a higher temperature was responsible for the higher loading of said pollutants. A study conducted in the petroleum refinery (S. Abdullah et al., 2018) and printing shop (Kiurski et al., 2016) revealed that in the processing industries, where a higher temperature was utilised in the production of goods, at such places emissions of gaseous pollutants were also found higher. In this study also thermal comfort factors were more dominant to the IAQ.

6. Conclusion

Indoor Air Quality (IAQ) of a textile dyeing and printing processing house was investigated in this study. In order to analyse the overall IAQ and identify the pollutants that contribute to the IAQ, two key essential process areas were considered. PCA was performed on the collected data in order to identify the key parameters that were responsible for pollutant emission in the indoor environment of the dyeing and printing processing house. Researches revelled that use of adhesives, solvents, dyes etc, under the high temperature undergoes chemical reactivity and responsible for the generation of TVOC, NO_2, and formaldehyes. All of these primary pollutants lead to the generation of O_3 in the indoor environment. Also, in the process micro particles of the dyes, fabrics, and pollutants emitted from the process, which forms the particulate matter concentration in the space. From the PCA loading plots of both the areas, it has been shown that parameters relating to thermal comfort, particle matter, NO_2, O_3, and TVOC are the most influencing parameters that contribute more to the IAQ. The utilisation of high temperatures and extensive amounts of heat were shown to play crucial roles in the emission of pollutants. This can be disclosed by the factor loading plot, as the all of the concern parameters were found to exhibit a positive link with one another. The rapid dispersion of pollutants is essential in order to reduce the amount of pollution within buildings. The successful management of a ventilation system, whether natural or forced, can be advantageous towards the achievement of an indoor environment that is to the satisfaction of the occupants.

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Data availability
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing Interest
The authors have no relevant financial or non-financial interests to disclose.

Authors' contribution
D V Jariwala performed the monitoring in the dyeing and printing house. He analysed all the data and prepared the manuscript according to the guidelines of the journal. Dr. R A Christian had read and edited the manuscript and agreed to the final version of the manuscript.

Declaration of conflicting interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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