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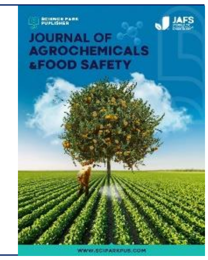

Journal of Agrochemicals and Food Safety

Relationship between rural environmental pollutants and psychological health

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Abstract

The current study aimed to survey various types of pollutants in the rural environment, explore people's perceptions of them, investigate the relationships between environmental pollutants and public health in these areas, and use artificial intelligence models to predict the connections among psychological disorders. This research was conducted in Al-Kom Al-Akhdar Village, Hosh Eissa, El-Beheira Governorate, Egypt. It identified several pollutants in the urban environment, including pesticides, exhaust emissions, agricultural and domestic waste, industrial activities, steady population growth, and solid waste dumping. Most participants experienced exposure to pollutants but did not engage in environmental protection efforts. However, the frequencies and percentages of participants aware of environmental sustainability were high. When considering future sustainable energy sources, the most mentioned options were solar and water energy. The most prevalent types of urban pollution include air, water, agricultural, and soil pollution. Artificial Intelligence (AI) was incorporated into this research, with four machine learning classifiers used to categorize the collected data: logistic regression, support vector machine, random forest, and decision tree. Participants recommended activities to reduce pollution, such as recycling, producing by-products, and safely disposing of household waste. Based on these findings, the researchers suggest further investigation into the effects of electronic devices on children and recommend repeating the current survey across different communities, whether urban or rural, to expand the dataset for machine learning classification and prediction. Linking biological activity to detected pollutant types could generate valuable data and lead to additional recommendations for managing pollutants.

Keywords: Rural Environment; Pollutants; Psychological Health; Artificial Intelligence (AI) Classifiers

1. Introduction

Rural environments are contaminated with diverse types of pollutants that affect water, soil, and air. Human activities, including urbanization and agricultural practices, contribute immensely to increasing pollutants in the environment, which might adversely affect ecosystems [1]. Major pollutants include emerging pollutants such as steroids, endocrine-disturbing compounds, pharmaceuticals, personal care products, artificial sweeteners, and surfactants. Mixtures of pollutants cause more adverse effects than individual compounds [2]. Industrialization, population growth, excessive use of pesticides and fertilizers, and leakage from water tanks are major sources of water pollution. These wastes have negative effects on human health [3, 4].

Additionally, stream water pollution caused by pesticides is a major environmental concern in farmed catchment areas. Many key factors contribute to this pollution, including weather, area topology, and crop management practices, all of which influence stream water quality [5, 6]. Thermal pollution damages water quality and ecosystem health [7]. It also causes the migration of creatures and can lead to the emergence of new species, disrupting reproduction and other biological processes [8, 9]. Furthermore, water pollution from plastics is significant, with about 280 million tons of plastic produced annually, much of which ends up in landfills and oceans [10]. Over 80% of sewage generated by human activities is discharged into rivers and oceans, resulting in environmental pollution and over fifty diseases [11]. Approximately 80% of diseases and 50% of child deaths worldwide are linked to poor water quality [12].

The health impacts of water pollution have been documented in the last several decades, including chronic poisoning, cancer related to microcystin, and health problems [13]. Water pollution has disastrous effects on infant mortality rates in peripheral and semi-peripheral countries [14, 15]. Long-term exposure to heavy metals may result in slowly progressing physical, muscular, and neurological degenerative processes that mimic Alzheimer's disease, Parkinson's disease, and muscular dystrophy [16]. With industrialization and urbanization, air pollution has become a life-threatening factor in many countries. Among air pollutants, the particulate matter with a diameter of less than 2.5 μm. It is a serious health problem because it might cause various respiratory and cardiovascular diseases [17, 18]. Worldwide, it was estimated that air pollution contributes to 800,000 premature deaths each year [19, 20]. The epidemiology and laboratory studies demonstrated that ambient air pollutants contributed to various respiratory problems, including bronchitis, emphysema, and asthma [3, 21, 22].

There was a notable spatial clustering effect on public health, with regional public health showing a convergence trend, and the adverse effects of air pollution’s negative externalities on public health were significant [17, 23]. Additionally, soil pollution affects soil, air, water quality, and people who live or work near polluted areas [24]. This type of pollution results from improper waste disposal, urbanization, agricultural chemicals, atmospheric decomposition, and soil erosion [25]. As urbanization increases, more people are exposed to environmental stressors, which can contribute to higher stress levels and compromised mental health [22, 26-29].

The associations between multiple environmental factors and self-assessed mental health for Chinese residents were significant [30]. Mental disorders have been associated with various aspects of anthropogenic changes to the environment, but the relative effects of different drivers were uncertain. Mental health disorders are generally linked to demographic and socioeconomic factors, and little is known about their interaction with the urban environment [30-32]. Contributions were made concerning both the perception of exposure to air pollution and the perception of the health effects associated with air pollution [33, 34]. Laboratory studies show that air pollutants can activate the neuroendocrine stress axis and modulate stress hormone levels, which could contribute to the development or exacerbation of psychological distress [31-37].

To predict and establish relationships between pollutants and mental health, artificial intelligence (AI) technology has become a necessity. It is widely used in variety of fields, including disease prediction, environmental monitoring, and pollutant prediction. There has also been an increase in the volume of research on air pollution using AI [38-43]. Perspectives of public understandings of global environmental risk have emphasized the interpretation and sense-making that takes place, modes of perception [44, 45], and the application of AI technologies and modules in studying the relationships between contaminants and mental health. For example, the water quality index was designed to describe various water quality variables using AI [46]. The impact of land use and management practices on stream water pollution was studied using modeling, simulation, and machine learning techniques to acquire knowledge about this complex domain. Results expressed the qualitative rules relating pollution factors to the temporal distribution of pesticide concentration [5].

Moreover, AI methods would enhance psychotherapy by providing therapists and patients with real or close-to-real-time recommendations [47, 48]. AI has been reported in

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various mental healthcare studies, where pertinent studies on the potential use of machine learning algorithms in assessing mental health [49]. Accordingly, the current study aimed to survey various types of pollutants in the rural environment, explore the perception of individuals on them, investigate the relationships between environmental pollutants and public health in these areas, and use artificial intelligence models in predicting the relationships among the presence of pollutants, mental health, and sustainability.

2. Materials and methods

2.1. Study location

This study was conducted in Al-Kom Al-Akhdar Village, Hosh Eissa, El-Beheira Governorate, Egypt (Figure 1).

2.2. Experimental design and questionnaire

The experimental descriptive analytical model was considered for the current pilot study because of its importance and widespread use in scientific research. It is one of the scientific research methods that is capable of accurately analyzing the problem or phenomenon of scientific research and identifying the reasons for its occurrence. The current research project was characterized by broad comprehensive responses from urban participants through a pre-designed and validated survey. Data was collected using a face-to-face personal interview with respondents using a pre-designed questionnaire form that was prepared to achieve the objectives of the research. Questionnaire content validity was constructed following the face validity method. The questionnaire was pre-tested on three hundred people and necessary modifications were amended. Then it was pre-tested with the responses of thirty persons, with necessary modifications carried out on the used form [50].

The questionnaire surveyed the demographic information: age, smoking, gender, marital status, possession of agriculture land, education level, occupation, volunteering with environmental protection agencies, suffering from pollution, culture, geographic openness, attendance of training courses related to environmental pollution, and sustainable development, sources of knowledge about environmental pollution and environmental sustainability, knowledge of environmental sustainability, environmental pollution and the relationship between pollution and individuals' mental health, global warming, and environmental pollutants, waste recycling is very important to reduce environmental pollution, public health and mental health and environmental pollutants, the most prevailing pollutants that affect the environment, the most common types of pollutants and psychological health, and how to reduce environmental pollution.

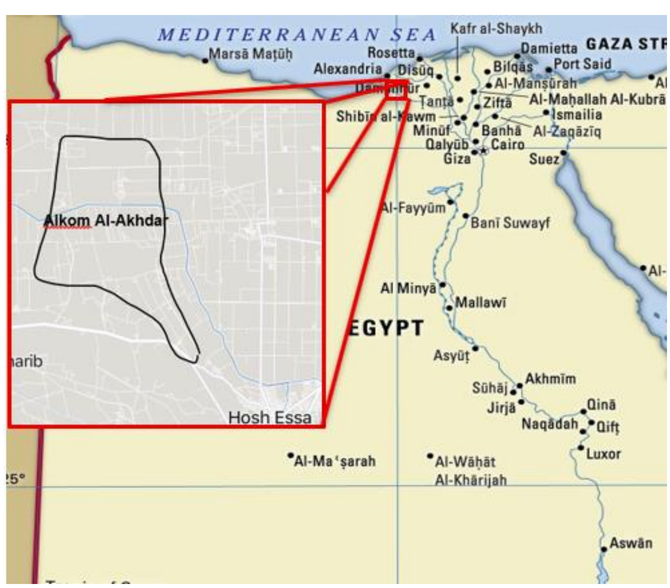

Figure 1. Map of the location of study (source: https://www.mapquest.com).

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2.3. Data analytics using statistical analysis and machine learning classifiers

2.3.1. Simple statistics

The questionnaire results were statistically analyzed using descriptive methods such as arithmetic mean, standard deviation, percentages, and frequencies. Quantitative statistical methods such as Pearson's simple correlation coefficient, correlation analysis model, and ascending progressive multiple regression were employed to explain and interpret the results. The Statistical Package for Social Sciences (IBM SPSS), version 25, was used.

2.3.2. Machine learning classifiers

Machine learning classifiers are algorithms used in Artificial Intelligence -Supervised Learning to categorize or classify data into predefined categories or labels. These classifiers are designed to make predictions based on patterns and features extracted from input data [51]. Four classifiers were evaluated in the current study, including the support vector machine (SVM), which tries to find the hyperplane that best separates the two classes [46, 52]. SVM is a powerful algorithm that works well in high-dimensional spaces and is widely used in various applications, including image classification, bioinformatics, and natural language processing. Logistic regression (LR) is a machine learning algorithm used for classification problems, where the goal is to predict binary class labels. It models the probability of the positive class as a function of the input variables using a logistic function, which maps any real-valued input to a probability between 0 and 1 [45]. Logistic regression uses maximum likelihood estimation (MLE) to learn the model parameters that maximize the likelihood of the observed data. Logistic regression is a simple yet effective algorithm that works well in many applications, including medical diagnosis, fraud detection, and credit scoring. Finally, the Random Forest algorithm (RF) is an ensemble learning algorithm that combines multiple decision trees to improve accuracy and reduce overfitting [41, 51, 53]. The algorithm involves two main steps: training and prediction. In the training step, a random subset of the training data was selected and for each subset, a set of features was randomly chosen. Then, a decision tree was built using the selected features and the subset of data. After that, the previous steps were repeated for a specified number of times (or until a stopping criterion was met). Finally, the decision trees were stored. In the prediction step, the new data points were run through each decision tree in the forest, and for each decision tree, the class of the data point was predicted based on the tree's decision rule. Then, the predictions from all trees were aggregated. After that, the majority vote for classification was done by taking the average of the predicted values for regression.

Evaluation matrices, also known as performance metrics, are used to assess the performance of machine learning models, algorithms, or systems. These metrics provide a quantitative measure of how well a model is performing in terms of accuracy (Equation 1). Precision: measures the proportion of true positives out of all positive predictions (Equation 2), recall: measures the proportion of true positives out of all actual positives (Equation 3), and F1 score, which is the harmonic mean of precision and recall and is a way to balance these two metrics (Equation 4). The choice of evaluation metrics depends on the specific problem and goals of the analysis. To evaluate the performance of the model that classifies current work, the following measures were used: Accuracy measures the percentage of correct predictions made by the model out of all predictions.

$$\boldsymbol{Accuracy} = \frac{true\ positives + true\ negatives}{true\ positives + false\ positives + true\ negatives + false\ negativess} \quad \text{Equation 1}$$

$$\boldsymbol{Precision} = \frac{\text{true positives}}{\text{true positives + false positives}} \quad \text{Equation 2}$$

$$\boldsymbol{Recall} = \frac{\text{true positives}}{\text{true positives + false negatives}} \quad \text{Equation 3}$$

$$\boldsymbol{F1\ Score} = \frac{\text{2 x (precision x recall)}}{\text{precision + recall}} \quad \text{Equation 4}$$

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3. Results and discussions

Distinctive description of participants: about 52.7% of participants were females, and 47.3% were males. The age of participants ranged from 18 to 70 years old, most of them (57.7%) were young (from 18 to 35 years) with an average of 38.8±15.8 years old (Table 1).

Data in Table 2 showed the percentages of the participants' occupations. Respondents of the survey were unemployed (33%), agriculture workers (26.7%), technicians (plumber, electrician) (11%), workers in agricultural trade (14.7%), technicians (in technology) (12%), and mining workers (2.7%).

Data in Table 3 showed the frequencies and percentages of smokers (nonsmokers, 63.0%), and smokers (37.0%), among participants. Also, 100% of participants suffer from one or more types of environmental pollutants.

Data in Table 4 showed that the categories of availability and use of knowledge sources were experienced by family and neighbors, television, radio, and agricultural extension engineers.

Table 1. The frequencies and percentages of gender, age, and spousal (social) status of participants in the current study (n=300).

Parameter	Frequency	Percentage
Gender		
Male	142	47.3
Female	158	52.7
Total	300	100
Age		
Young	173	57.7
Adult	94	31.3
Aged	33	11.0
Total	300	100
Marital Status		
Married	204	68.0
Single	92	30.7
Widow	3	1.0
Divorced	1	0.3
Total	300	100

Source: Collected and calculated from the questionnaire conducted in the current study.

Table 2. Frequencies and percentages of occupation and possession of agricultural land of participants in the current research study.

Parameter	Frequency	Percentage
Occupation		
Unemployed	99	33.0
Agricultural worker	80	26.67
Technicians (plumber, electrician, etc.)	33	11.0
Workers (traders)	44	14.7
Technician (technology agent)	36	12.0
Mining worker	8	2.7
Total	300	100
Possession of agricultural land		
Possess	95	31.7
no possession (rent)	205	68.3
Total	300	100

Source: Collected and calculated from the questionnaire conducted in the current study.

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The Ministry of Environment website, the agricultural extension magazine bulletins, the extension magazine, the extension meeting, agricultural researchers, university professors, scientific research articles, and social networking sites. The percentage of reading and seeking information sources was 1, 91, and 8% in the low, middle, and high categories, respectively. Also, data in Table 4 showed cultural openness, which is the extent of people's culture, knowledge, and reading, following local and international news, using the internet for information and education, attending educational seminars at the university, learning about different cultures, and participating in exploratory trips for cultural development. These were classified into low, middle, and high, 1.3, 80.3, and 18.3%, respectively. Moreover, data on geographical openness showed that travel either outside the country, to the capital, to neighboring governorates' centers, and to the villages of the centers seeking knowledge on the environment and pollution. Data was categorized as low, middle, and high, with 6.3, 73.0, and 20.7%, respectively.

Table 3. Frequency and percentages of the incidence of smoking, suffering from pollution, and volunteering in activities to help protect the environment from pollution among respondents (n= 300).

Parameter	Frequency	Percentage
Smoking		
Non smoker	189	63.0
Smoker	111	37.0
Total	300	100.0
Suffering from pollution		
Suffer	300	100.0
No effect	0	0
Volunteering to protect the environment		
Volunteer	0	0
Don't Volunteer	300	100.0

Source: Collected and calculated from the questionnaire conducted in the current study.

Table 4. Frequencies and percentages of knowledge, cultural openness to others, and geographical openness to get information on pollution and psychological health (n=300).

Parameter	Frequency	Percentage
Knowledge		
Low	3	1.0
Middle	273	91.0
High	24	8.0
Total	300	100.0
Mean ±SD	19.15±3.86	
Cultural openness		
Low	4	1.3
Middle	241	80.3
High	55	18.3
Total	300	100.0
Mean ±SD	9.76±2.62	
Geographical openness		
Low	19	6.3
Middle	219	73.0
High	62	20.7
Total	300	100.0
Mean ±SD	8.60±2.89	

Source: Collected and calculated from the questionnaire conducted in the current study.

Data in Table 5 collectively presented a description of participants' demographics, habits, education, and cultural interaction with information on pollutants and how they cope with them. Participants were mainly young (average age was 38±15 years), most of them were married, and worked in their own land. Educated persons were surveyed (12.63±4.78). Also, the table introduces the results of how they manifest pollution, cultural and geographical openness, learning through attending seminars, and training sessions that would impact their knowledge of environmental sustainability.

Data in Table 6 showed several types of pollutants that mostly affect the environment, from the greatest pollutants to the least. Pesticides, exhaust of vehicles, and fossil fuel consumption were the greatest sources of contamination that exert effects on the environment (100% of participants), followed by, in descending order, agricultural and domestic wastes, industrial waste, deforestation, population growth, solid waste, plastics, urbanization, and overfishing, according to 96.6, 90, 81.3, 73.6, 54.7, 50, 40, and 38% of participants, respectively.

Data in Table 7 showed the responses of participants about the most common type of pollution found in the environment (air:100, water: 94, agricultural soil pollution: 88.3, visual: 83.3, noise: 76.6, electronic (waste leftovers from damaged devices: 70, radioactive: 60, and plastic: 46.6%). Also, data in Table 8 showed sources of air pollution in the studied area were pesticide application (100%), chemicals and fertilizers (95.3%), factory fumes (88%), vehicle emissions and exhausts (84.3%), fires and smoke (47.6%), sewage (48%), smoke from burning household wastes and peat moss manufacturing (31.1%), and home ovens and stoves started with hay and debris of crops (29.3%).

Data in Table 9 showed the percentages of participants who have knowledge about environmental sustainability. They were categorized into 84.7, 15.3, and 0 % with middle, high, and low knowledge. Also, their attitudes towards the achievement of environmental sustainability (middle: 57.0, high: 43.0, low: 0).

Data in Table 10 showed diverse sources of water pollution in the area studied. Waste from factories and foundries thrown into water sources (97.3%), agricultural drainage (96%), getting rid of dead animals and wastes (80%), human waste (73%), and detergents (60.6%) were the major pollutants.

Table 5. Collective descriptive statistics of studied demographics, attitudes, and willingness to protect the environment from several types of pollutants.

Parameter	Min	Max	Mean	±SD
Age	14.00	87.00	38.80	15.80
Marital status	1.00	4.00	1.72	0.52
Possession of agricultural land	1.00	2.00	1.32	0.47
Gender	1.00	2.00	1.53	0.50
Education level	0.00	24.00	12.63	4.79
Occupation	1.00	7.00	3.27	2.14
Smoking	0.00	4.00	1.38	0.51
Volunteer for environmental protection	1.00	1.00	1.00	0.00
Manifestation of pollution	2.00	2.00	2.00	0.00
Cultural openness	2.00	18.00	9.76	2.62
Geographical openness	1.00	15.00	8.60	2.89
Attending seminars	1.00	1.00	1.00	0.00
Lack of training	0.00	1.00	0.94	0.23
Degree of exposure to information sources	8.00	36.00	19.15	3.83
Knowledge of environmental sustainability	28.00	39.00	32.47	1.96
Total trend	37.00	45.00	40.36	1.35

N = 300; descriptive analysis was performed using the Statistical Package for Social Sciences (SPSS) package.

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Table 6. The frequencies and percentages of the types of pollutants that have the most impact on the environment are organized from the greatest to the lowest.

Parameter	F	%
Use of agricultural pesticides	300	100
Exhaust from vehicles, trains, ships, and airplanes	300	100
Fossil fuel combustion	300	100
Agricultural and domestic waste	290	96.6
Industrial activities	270	90.0
Deforestation	244	81.3
Steady population growth	221	73.6
Dumping solid waste	154	54.7
Plastic consumption	150	50.0
Rapid urbanization	120	40.0
Overfishing	114	38.0

Table 7. The frequencies and percentages of the most common types of pollutants found in the studied environment are organized from the greatest to the lowest.

Pollutants	Frequency	%
Air	300	100
Water	282	94.0
Agricultural soil	265	88.3
Visual	250	83.3
Noise	230	76.6
Electronic*	210	70.0
Radioactive	180	60.0
Plastic	140	46.6

*Waste from leftovers of damage and the recycling of electronic devices.

Source: Collected and calculated from the questionnaire conducted in the current study.

Table 8. Sources of air pollution in the studied area, according to the responses of survey respondents, were arranged from the greatest to the lowest.

Contaminant	F	%
Pesticides	300	100.0
Chemicals and fertilizers	286	95.3
Factory fumes	264	88.0
Car emissions and exhaust	253	84.3
Smoke from fires	143	47.6
Sewage	114	38.0
Smoke from burning household waste and bitmoss manufacturing	94	31.1
Home ovens and stoves started with hay and debris from crops	88	29.3

Source: Collected and calculated from the questionnaire conducted in the current study.

Collectively, according to the opinions of the surveyed participants, the sustainable alternatives of energy sources were required and included sun (100%), wind (99.7%), water (93.7%), natural gas (20%), coal (15.3%), ethanol (12%), electricity (8.7%), and nuclear (5.3%) (Table 11).

The relationships between individual factors and citizens'

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knowledge and attitudes towards environmental sustainability were presented in Table 12. Pearson correlation analysis between individuals' factors showed significant positive relationships between the degree of education level and citizens' knowledge of environmental sustainability, which means that educated people have a satisfactory level of knowledge about environmental sustainability.

There was also a significant positive correlation between the availability of information about environmental sustainability and both the knowledge and attitudes of citizens toward it (Table 12), which shows that the availability of sources of information about environmental sustainability increased the citizens' knowledge and attitudes toward it.

Table 9. Frequencies and percentages of knowledge levels of participants on environmental sustainability and their attitude toward achieving a sustainable environment.

Parameter	Frequency	Percentage
Knowledge of sustainable environment		
Middle	254	84.7
High	46	15.3
Low	0	0
Total	300	100.0
Mean ± SD	32.47±1.96	
Attitudes toward environmental sustainability		
Middle	171	57.0
High	129	43.0
Low	0	0
Total	300	100.0
Mean ± SD	40.36±1.35	

Source: Collected and calculated from the questionnaire conducted in the current study.

Table 10. Frequencies and percentages of sources of water pollution in the studied location, arranged from the greatest to the lowest.

Source of water pollution	F	%
Waste from factories and foundries dumped into water sources	292	97.3
Agricultural drainage	288	96.0
Throwing dead animals and their leaves into freshwater sources	240	80.0
Ammonia gas leakage from human waste	219	73.0
Industrial detergents	182	60.6

Table 11. Frequencies and percentages of more sustainable alternative energy sources in the coming decades, arranged from the greatest to the lowest.

Parameter	F	%
Sun	300	100.0
Wind	299	99.7
Water	281	93.7
Natural gas	60	20.0
Coal	46	15.3
Ethanol	36	12.0
Electricity	26	8.7
Nuclear	16	5.3

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Pearson's correlation coefficients of education level and information resources were 14.1 and 14.4%, respectively, with citizens' knowledge of environmental sustainability. Also, cultural mobility and availability of various sources of information were correlated with the attitudes of participants by 16.1 and 18.1%, respectively. Also, multiple regression results revealed that education level and information resources would predict approximately 3.8% of citizens' knowledge of environmental sustainability (Table 13).

Multiple regression results revealed that two variables, cultural mobility and information resources, would predict approximately 4.6% of citizens' attitudes toward environmental sustainability (Table 14).

Table 12. Pearson correlation coefficients between individuals' factors of citizens' knowledge and attitudes towards environmental sustainability.

Variable	R^2	
	Knowledge	**Attitude**
Age	0.020^{ns}	0.032^{ns}
Education Level	0.141*	
Degree		0.106^{ns}
Cultural Mobility	0.006^{ns}	0.161**
Information	0.144*	
Resources		0.181**
Geographical	0.015^{ns}	
Mobility		0.039^{ns}

*P≤0.05, **P≤0.01%, ns: not significant

Data in Table 15 showed the percentages and frequency of participants who see an impact of pollutants on public health (middle effect: 58.0% and high effect: 100.0%). Pearson correlation coefficients between the degree of presence of environmental pollutants and the mental health of citizens. Additionally, data in Table 16 and Figure 3 showed that all participants thought that pollutants significantly affect mental health. Multiple regression results revealed that the degree of presence of environmental pollutants would predict approximately 7.9% of the mental health of citizens. Pearson correlation analysis (Table 15) showed positive, statistically significant relationships between the degree of presence of environmental pollutants and the mental health of citizens. This means that the more pollutants in the environment, the more this is linked to the mental health of the citizens.

Data in Figure 2 showed percentages of mentally ill and normal people. Most of the participants (78.3%) were classified as normal according to their responses to the survey. Only 2% were classified as not ill, and about 19.7% of them were categorized as having some sort of mental illness.

The collected dataset preparation phase takes significant processing time; the preprocessing phase includes several steps, such as cleaning data, handling missing values, normalizing or scaling features, and encoding categorical variables. Each step helps improve the dataset so that the machine learning algorithms can interpret the data correctly and effectively.

Table 13. Multiple regression analysis between variables that were significantly related to citizens' knowledge of environmental sustainability.

Variable	B	T	R^2	F	Sig
Education level degree	0.54	2.31			
			0.038	5.8	0.00
Information resources	0.69	2.38			

Constant = 30.4, Y= 30,4+054 X_1+0.069 X_2, where X_1=education level degree, and X_2=information resources.

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Table 14. Multiple regression analysis between variables that were significantly related to citizens' attitudes toward environmental sustainability.

Variables	B	T	R^2	F	Sig
Information recourses	0.05	2.5			
			0.046	7.2	0.00
Cultural mobility	0.06	2.0			

Constant =38.7, Y =30.4+0.05 X_1+0.06 X_2, where X_1= information resources, and X_2= cultural mobility.

Table 15. The impact of pollutants on mental health and Pearson correlation coefficients between pollutants and mental health.

	Frequency	Percent	Valid Percent
Strong effect	174	58.0	58.0
Medium	126	42.0	42.0
Total	300	100.0	100.0
Pearson correlation coefficients between environmental pollutants and mental health			
Variables	Pollutants (R^2)		
Mental health of citizens	0.281**		

*P<0.05, **P<0.01

Table 16. The effect of pollutants on mental health and the multiple regression analysis between the degree of presence of environmental pollutants and the mental health of citizens.

Effect	F		%	Valid %	
Strong	300		100.0	100.0	
Variable	**B**	**T**	**R^2**	**F**	**Sig**
Degree of presence of environmental pollutants	0.476	5.06	0.079	25.6	0.00

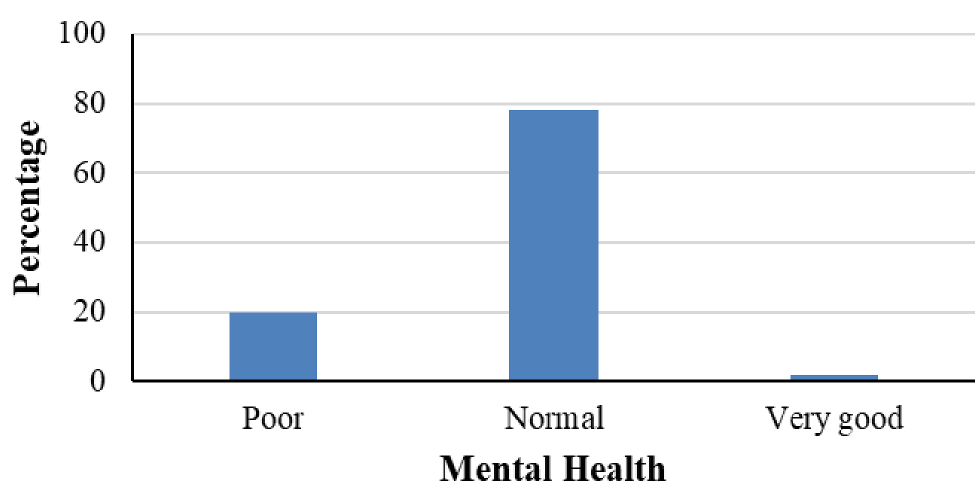

Figure 2. Percentages of the presence of mental health due to the presence of environmental pollutants.

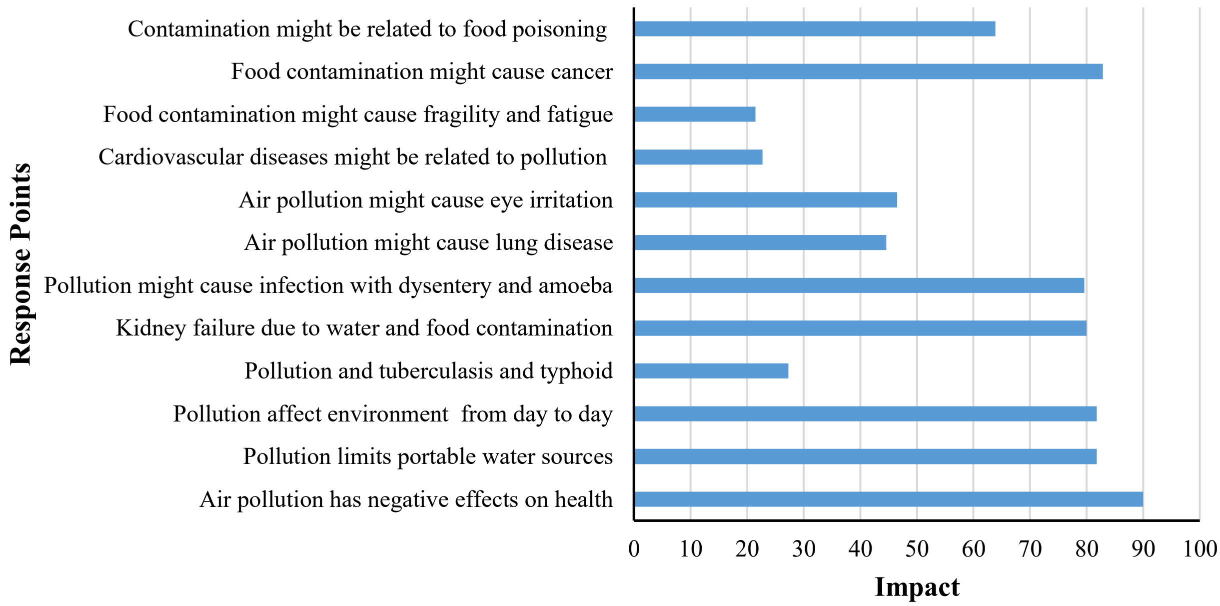

Figure 3. Percentages of impact of pollutants on public health based on responses of participants.

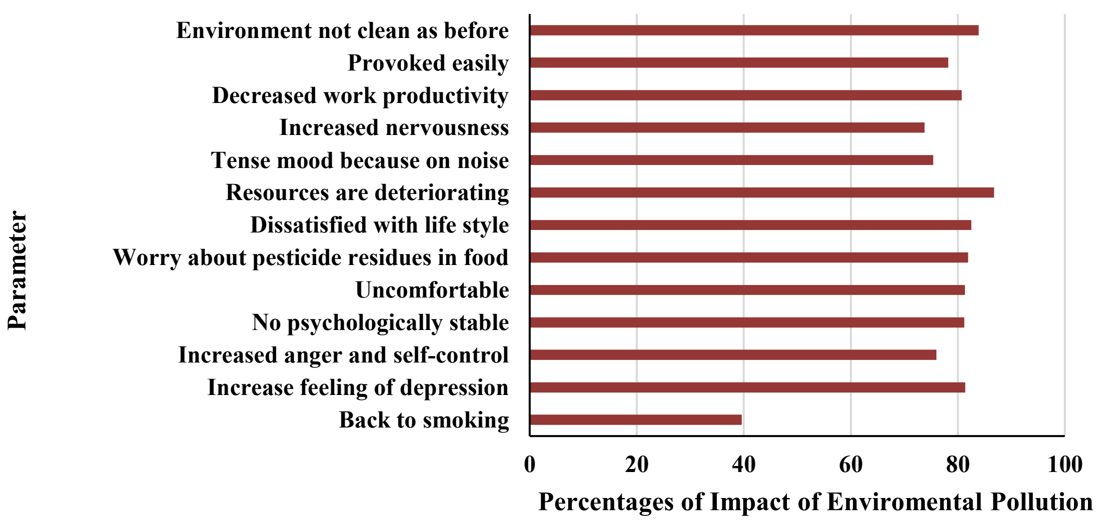

Figure 4. Impact of pollutants on mental health on daily activity.

Data in Figures 3, 4, and 5 after applying the machine learning models showed the pollutants that mostly affected the environment arranged in descending order from most influential to least influential as follows dumping of solid waste, agricultural and household waste and not to be recycled, spaying agriculture pesticide, exhausts from vehicles, trains, ships and aircraft, rabid urbanization, overfishing, deforestation and trees, plastic consumption, fossil fuel combustion and steady population growth. The results provided describe an experimental assessment of pollutants affecting the environment, with an arrangement in descending order from the most influential to the least influential.

The most common types of pollution found in the environment (Figure 6) were air pollution (12%), water pollution (12%), agricultural soil pollutants (14%), noise (12%), and visual pollution (12%). The provided results present the distribution

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of several types of pollution in the environment, with each type representing a percentage of the total pollution. The 12% allocation to water pollution suggests that a portion of the total pollution affects water bodies such as rivers, lakes, and oceans. Agricultural soil pollution accounts for 14% of the overall pollution. This type of pollution is associated with the introduction of contaminants into the soil through agricultural practices. Pesticides, fertilizers, and chemicals used in farming can contribute to soil pollution, affecting soil health, and potentially affecting crops and ecosystems. Noise pollution, being 12% of the total pollution, involves the presence of unwanted or harmful sounds in the environment. Visual pollution, accounting for 12% of the total, refers to the presence of unsightly or visually intrusive elements in the environment. This can include factors such as litter, poorly maintained structures, and other visual disturbances.

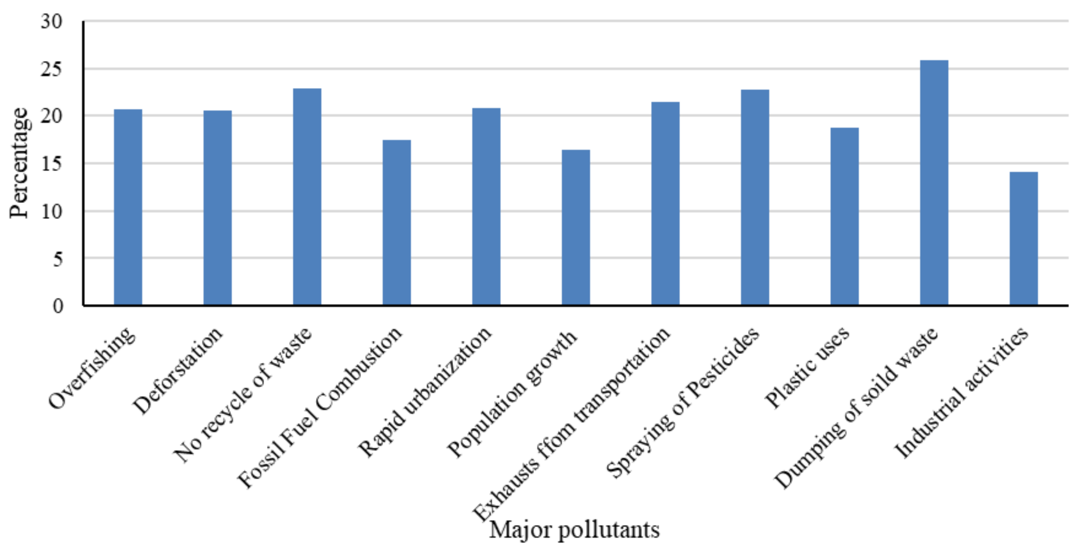

Figure 5. Major pollutants mostly affect the environment. rabid.

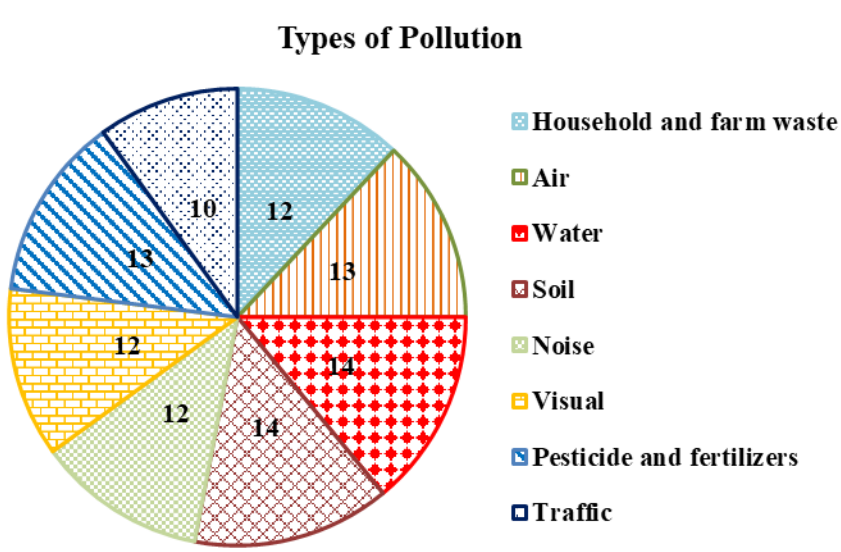

Figure 6. Most common type of pollution in the environment.

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In Figure 7, the sources of air pollution include kiln smoke in 12%, chemical industries (foundries) and chemical fertilizers in 14%, and fires and smoke in 13%. The results presented in the figure outline the sources of air pollution and their respective contributions in terms of percentages. Kiln smoke represents 12% of the total air pollution. Kilns are furnaces or ovens used for various industrial processes such as the production of ceramics, cement, and lime. The combustion of fuels in kilns can release pollutants into the air, including particulate matter, sulfur dioxide, and other harmful substances. The 12% allocation suggests that this specific source significantly contributes to overall air pollution.

Chemical industries, including foundries, and the use of chemical fertilizers collectively contribute to 14% of air pollution. Foundries are industrial facilities involved in metal casting, and their operations can release pollutants into the air, such as metal dust and emissions from metal smelting. Chemical fertilizers, when applied to agricultural fields, can release ammonia and nitrogen oxides into the air. The combined 14% highlights the impact of industrial and agricultural activities on air quality. Fires and smoke contribute to 13% of air pollution.

Common water pollutants (Figure 8) were residues of factories and foundries that are thrown into water sources (26%), leakage of ammonia gas from human waste (21%), industrial detergents (26%), and dumping of dead animals and their remains in freshwater sources (27%). It's important to note that these results highlight anthropogenic sources of water pollution, underscoring the importance of proper waste management, industrial practices, and pollution prevention strategies to protect and preserve water quality.

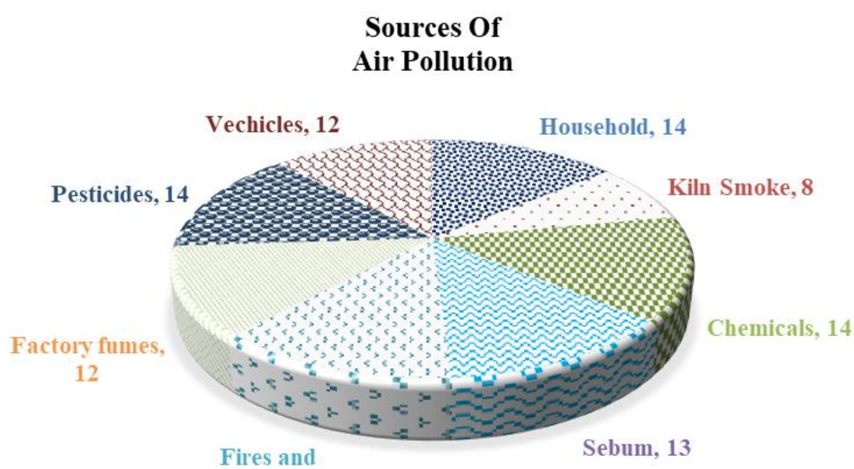

Figure 5. Various sources of air pollutants.

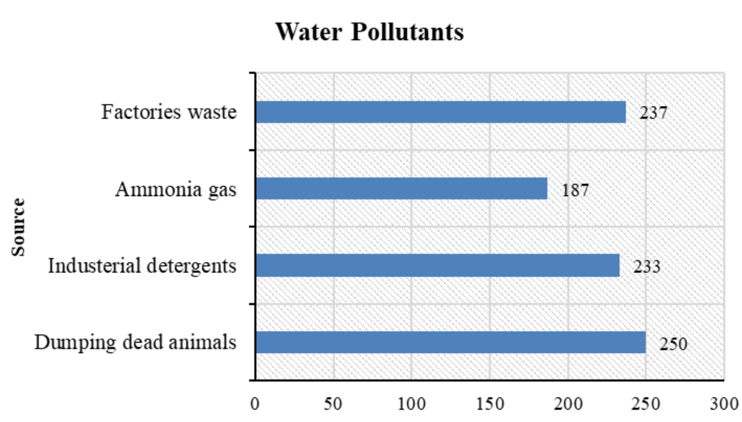

Figure 6. Sources of water pollution.

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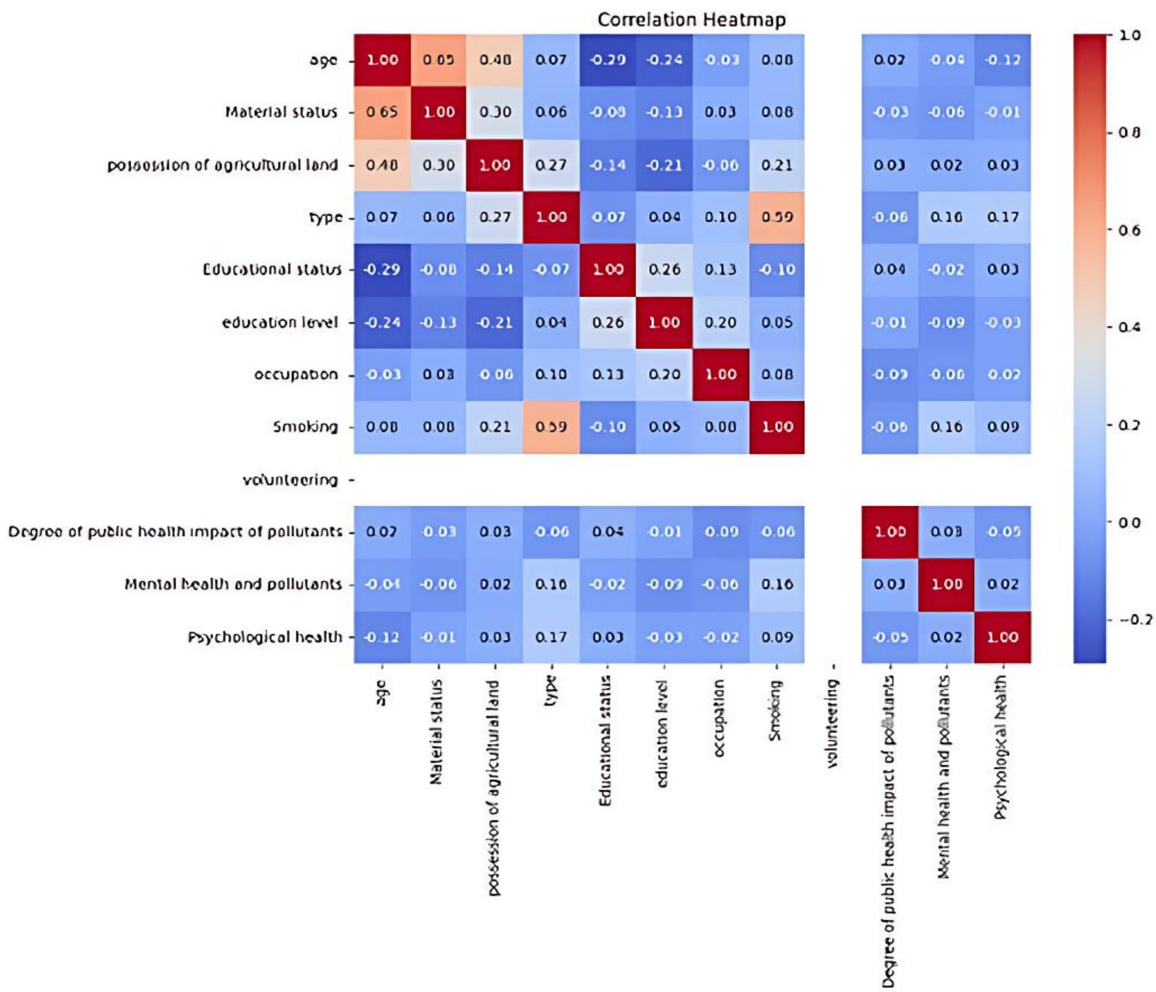

Figure 7. Correlation heatmap of the most affecting variables.

Collectively, Figure 9 shows the correlation heatmap of main factors affecting the relation between presence of pollutants and mental health of rural inhabitants.

Moreover, the SVM classified and predicted the mental health outcomes based on exposure to pollutants. Relevant features that might affect mental health outcomes include specific pollutants, demographic information, or other relevant variables. The model was evaluated using proper metrics (accuracy, precision, recall, and F1-score) to generalize for unseen data. It was clear from the data in Figure 10 A that the accuracy rate, precision, recall, and F1-score of the SVM were 70, 49, 70, and 58%, respectively. Also, decision tree classifier provided interpretability of the understanding of factors that influence mental health outcomes (Figure 10 B). Decision tree classifier proceeded with relevant features that might impact mental health outcomes, including specific pollutants and demographic information, using the decision tree model on the testing set, using appropriate metrics (accuracy, precision, recall, and F1-score with 62, 57, 61, and 58%, respectively.

Random Forest classifier studied the relationship between mental health and pollutants and offered robust insights. Figure 10 C showed that the accuracy rate of the random forest classifier was 65%, the precision was almost 54%, the recall was 65% and F1-score was almost 57%. Logistic regression tree classifier: Logistic regression tree (LRT) is in the context of a decision tree-based ensemble model, like a Gradient Boosting Machine (GBM), or an Adaptive Boosting (AdaBoost) classifier for studying mental health and pollutants (Figure 10 D). The accuracy rate of the logistic regression forest classifier was 70%, the precision was 49%, the recall was 70%, and F1-score was almost 57%. Collectively, the four classifiers were compared in Figure 10. Based on the earlier

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results, it could be concluded that the best classifiers in terms of accuracy were SVM and logistic regression. Logistic regression and SVM prevailed according to recall percentages. Finally, the decision tree classifier was the best choice in terms of F1-score.

Data in Table 17 showed the suggestions and solutions for preserving good mental health in relation to environmental pollutants from the point of view of the citizens surveyed. Some solutions at the individual level to reduce the presence of pollutants were: rationalizing the use of environmental resources and not wasting them, recycling household waste to create useful by-products, and not throwing dead animals into waterways.

In Table 18, some of the suggested solutions are provided by participants to reach sustainability and environmental protection. Research results showed suggested views arranged from the most popular to the least as the following: increase the environmental awareness among children from a young age in schools (100%), cash in return of waste recycling (97%), reduction of greenhouse gas emissions (96%), use of renewable and sustainable energy sources (94.6%), implementing fines and raising their value to reduce the burning of rice straw and infringement on the agricultural environment (91.6%), activating environmental laws to reduce pollution (90%), activating the role of civil society organizations to spread awareness of climate change issues and environmental pollution (87.3%), conducting guidance seminars to raise awareness of the dangers of climate change (85%), cooperation between government agencies, the environment, and civil society organizations (83.6%), enacting laws that criminalize the excessive use of pesticides and chemical fertilizers beyond the recommended levels (82.6%), issue fines and criminalize harvesting crops before the end of the pesticide safety period in order to ensure food safety (80.6%), good urban planning that allows the spread of green areas (78.3%), encouragement organic farming methods to preserve agricultural resources from pollution (75%), and deploying waste collection units in all suburbs and regions to reduce pollution and facilitate recycling (73.3%).

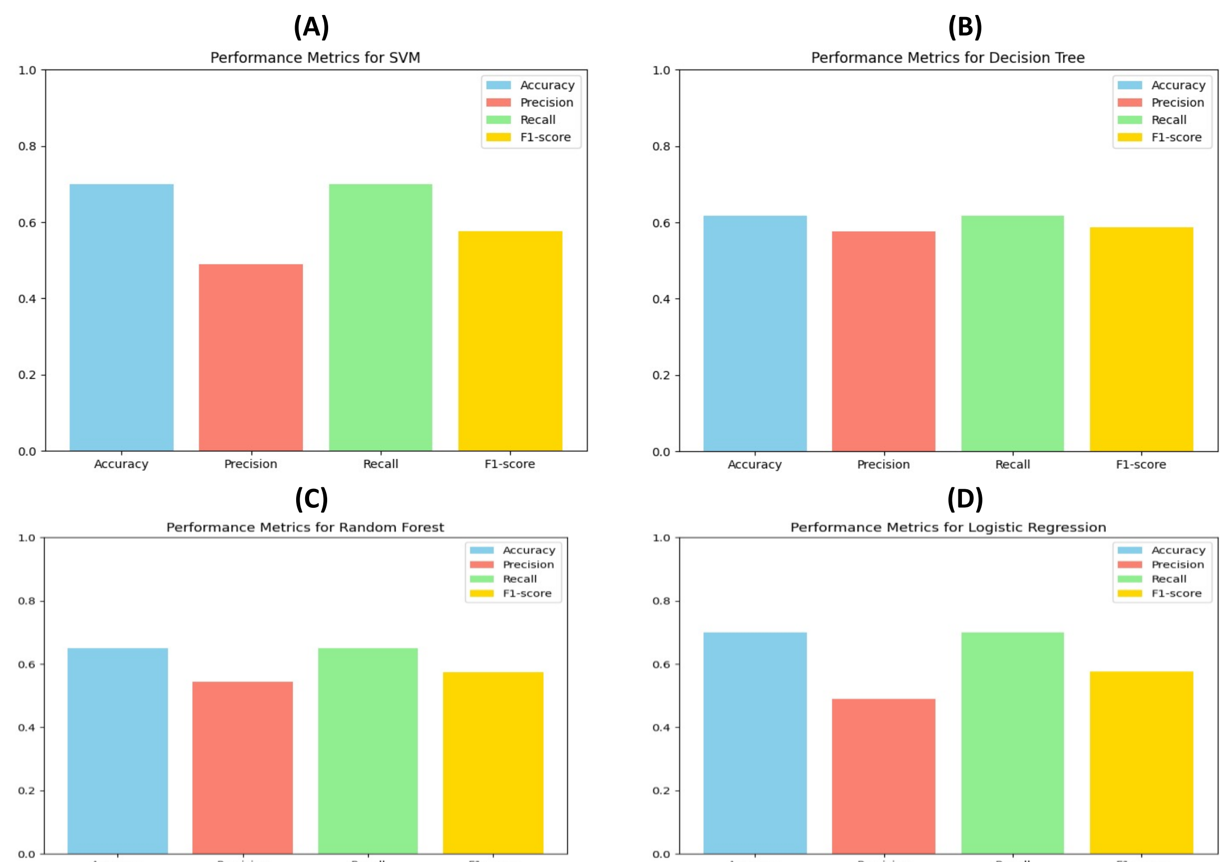

Figure 8. Performance metrics of Support Vector Machines (SVM) classifier (A), the decision tree (B), random forest (C), and logistic regression (D) classifiers on the relation between mental health and pollutants.

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Table 17. Suggestions and solutions for preserving good mental health in relation to environmental pollutants.

Task	F	%
Rationalizing the use of environmental resources and not wasting them	285	95.0
Recycling household waste to create useful by-products	277	92.3
Do not throw dead animals and birds into waterways	265	88.3
Safe disposal of household waste	260	86.6
Separating organic waste from solid waste in special containers	254	84.6
Separate plastic and paper waste for easy recycling	243	81.0
Contributing to street landscaping through personal efforts	221	73.6
Use environmentally friendly products and resources to preserve it	174	58.0
Adopting integrated pest control management	160	53.3
Reduce the use of chemical fertilizers	153	51.0
Contributing to volunteer work for environmental sustainability	142	47.3
Do not catch fish with pesticides	134	44.6

Table 18. Some suggested solutions and activities provided by participants to reach sustainability and environmental protection.

Task	F	%
Spread environmental awareness among children from a young age in schools	300	100
Cash in return for waste recycling	291	97.0
Reduction of greenhouse gas emissions	288	96.0
Use and provide renewable and sustainable energy sources	284	94.6
Implementing fines and raising their value to reduce the burning of rice straw and infringement on the agricultural environment	275	91.6
Activating environmental laws to reduce pollution	270	90.0
Activating the role of civil society organizations to spread awareness of climate change issues and protect the environment from pollution	262	87.3
Conducting guidance seminars to raise awareness of the dangers of climate change and environmental pollution	255	85.0
Cooperation between government agencies, the environment, and civil society organizations to spread a culture of environmental sustainability	251	83.6
Enacting laws that criminalize the excessive use of pesticides and chemical fertilizers beyond the recommended levels	248	82.6
Activate fines and criminalize harvesting crops before the end of the pesticide safety period to ensure food safety	242	80.6
Good urban planning that allows the spread of green areas	235	78.3
Follow organic farming methods to preserve agricultural resources from pollution	225	75.0
Deploying waste collection units in all suburbs and regions to reduce pollution and facilitate recycling	220	73.3

The current study examined the relationship between the presence of environmental pollutants and the awareness of urban inhabitants of these pollutants and their psychological status. To the best of our knowledge, this work is one of the earliest types of research done to address these objectives. Similar to the data reported herein, interviews with members of the public about urban air pollution concluded that location, and understanding of the immediate physical, social, and cultural landscape [44]. Participants were rural inhabitants with ages ranging from ≤ 20 to > 60 years. Most of the participants were female (51.476%), and the studied population was married people (82.364%) which was higher than our results (68%) [31]. The studied population herein agreed that the age of a survey performed among the Belgian population was over 15 years old [37]. According to the present results, about one-third of the respondents were smokers, but all of them mentioned that they suffer from pollution. These data agreed with the survey conducted by Yang et al, where, 47.029% of respondents were living in urban areas and 30.243% were smoking [31].

The increasing water contamination caused by discharging untreated effluent is a major problem faced by humanity worldwide [1]. For this, government authorities and other organizations are concerned about cost-effective wastewater treatment technology to overcome water pollution and water shortage problems for humans and biodiversity [11]. The industrial, agricultural, and solid wastes were directly dumped into rivers, which made them highly polluted and poisonous for humans and aquatic creatures [54].

The public health impact of air pollution on physical health is increasingly studied, and it is emphasized that improved air quality is associated with a range of quantifiable health benefits. The World Health Organization (WHO) recently ranked air pollution as the major environmental cause of premature death [36]. The relationship between air pollution and mental health, as well as the regulatory effects of health behaviors, was reported using the Center for Epidemiologic Studies Depression (CES-D) scale [31]. Also, data reported by other researchers agreed with the present survey results on soil pollution. Industrial wastes such as harmful gases and insecticides are the most common causes of soil pollution. Supporting natural decomposition processes has the potential to serve as a cost-efficient method to reduce the risks of contaminated soils [5, 55]. Pollution reduces the soil's ability to yield food [56, 57].

Microplastics and traffic pollutants resulted in a moderation of the values for the respective pollution indicators for all heavy metals, while in the period before the peak, there was a continuous upward trend [58, 59]. Plastic pollution creates several kinds of negative consequences combined with ecological and socioeconomic effects, toxicological effects via ingestion of plastics and rafting of organisms, provision of new habitats, and introduction of invasive species, which are significant ecological effects with growing threats to biodiversity and trophic relationships [60]. Considerable attention has been given to govern the toxic elements related to e-waste materials and their effective management and recycling practices [61]. Acute and mental health symptoms were observed among farmers and helpers. Symptoms and exposure data were collected by interviews, and mental health outcomes by the Self-Reporting Questionnaire [62].

Panelists indicated that the water problems were the root of increased stress. Prolonged or chronic stress has the potential to lead to severe physical health outcomes such as cardiovascular disease [63]. High exposure to pesticides must be a major public health concern because it reduces farmers' quality of life [62].

4. Conclusion

The current study screened the several types of pollutants in the urban environment (pesticides, exhausts, agricultural and domestic waste, industrial activities, and dumping solid wastes). Most of the participants suffered from exposure to pollutants, but they never volunteered to protect the environment. Frequencies and percentages of participants with knowledge of environmental sustainability were high among participants. Frequency and percentages of more sustainable alternative energy sources in the coming decades (sun and water). Most common types of pollution in urban environment were air, water, agricultural, and soil. Four related classifiers were tried to classify the data including, SVM and logistic regression. Participants recommended adopting activities that reduce the presence of pollutants, such as recycling, manufacturing of by-products, and disposing of household waste safely.

Conflict of interest statement

The authors declare that they have no conflict of interest.

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Data availability

Data will be available on request.

References

[1] Kılıç, Z. (2021). Water pollution: causes, negative effects and prevention methods. İstanbul Sabahattin Zaim Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 3(2), 129-132. https://doi.org/10.47769/izufbed.862679

[2] Madhav, S., Ahamad, A., Singh, A. K., Kushawaha, J., Chauhan, J. S., Sharma, S., & Singh, P. (2020). Water Pollutants: Sources and Impact on the Environment and Human Health. In: Pooja, D., Kumar, P., Singh, P., Patil, S. (eds) Sensors in Water Pollutants Monitoring: Role of Material. Advanced Functional Materials and Sensors. Springer, Singapore, 21-41. https://doi.org/10.1007/978-981-15-0671-0_3

[3] Haseena, M., Malik, M. F., Javed, A., Arshad, S, & Asif, N (2017). Water pollution and human health. 1(3), 16–19. https://doi.org/10.4066/2529-8046.100020

[4] Al-Taai, S. H. H. (2021). Water pollution Its causes and effects. In IOP Conference Series: Earth and Environmental Science, 790 (1), 012026. https://doi.org/10.1088/1755-1315/790/1/012026

[5] Cordier, M. O., Garcia, F., Gascuel-Odoux, C., Masson, V., Salmon-Monviola, J., Tortrat, F., & Trépos, R. (2005). A machine learning approach for evaluating the impact of land use and management practices on streamwater pollution by pesticides. MODSIM 2005 International Congress on Modelling and Simulation, 2651–2657.

[6] Konstantinou, I. K., Hela, D. G., & Albanis, T. A. (2006). The Status of pesticide pollution in surface waters (Rivers and Lakes) of Greece. Part I. Review on Occurrence and Levels. Environmental Pollution, 141(3), 555-570. https://doi.org/10.1016/j.envpol.2005.07.024

[7] Abdi, R., & Endreny, T. (2019). A river temperature model to assist managers in identifying thermal pollution causes and solutions. Water, 11(5), 1060. https://doi.org/ 10.3390/w11051060

[8] Raptis, C. E., van Vliet, M. T., & Pfister, S. (2016). Global thermal pollution of rivers from thermoelectric power plants. Environmental Research Letters, 11(10), 104011. https://doi.org/10.1088/1748-9326/11/10/104011

[9] Abbaspour, M., Javid, A. H., Moghimi, P., & Kayhan, K. (2005). Modeling of thermal pollution in coastal area and its economical and environmental assessment. International Journal of Environmental Science & Technology, 2(1), 13-26. https://doi.org/10.1007/BF03325853

[10] Sigler, M. (2014). The effects of plastic pollution on aquatic wildlife: current situations and future solutions. Water, Air, & Soil Pollution, 225(11), 2184. https://doi.org/10.1007/s11270-014-2184-6

[11] Jayaswal, K., Sahu, V., & Gurjar, B. R (2018). Water pollution, human health and remediation. In S. Bhattacharya, A. B. Gupta, A. Gupta, & A. Pandey (Eds.), Water remediation, 11–27. Springer Singapore. https://doi.org/10.1007/978-981-10-7551-32

[12] Lin, L., Yang, H., & Xu, X. (2022). Effects of water pollution on human health and disease heterogeneity: a review. Frontiers in environmental science, 10, 880246. https://doi.org/10.3389/fenvs.2022.880246

[13] Lu, W. Q., Xie, S. H., Zhou, W. S., Zhang, S. H., & Liu, A. L. (2008). Water pollution and health impact in China: a mini review. Open Environmental Sciences, 2(1), 1-5. https://doi.org/10.2174/1876325100802010001

[14] Jorgenson, A. K. (2004). Global inequality, water pollution, and infant mortality. The Social Science Journal, 41(2), 279-288. https://doi.org/10.1016/j.soscij.2004.01.008

[15] Xu, C., Xing, D., Wang, J., & Xiao, G. (2019). The lag effect of water pollution on the mortality rate for esophageal cancer in a rapidly industrialized region in China. Environmental Science and Pollution Research, 26(32), 32852-32858. https://doi.org/10.1007 /s11356-019-06408-z

[16] Verma, R., & Dwivedi, P. (2013). Heavy metal water pollution-A case study. Recent research in Science and Technology, 5(5), 98–99. https://updatepublishing.com/journal/index.php/rrst/article/view/1075

[17] Feng, Y., Cheng, J., Shen, J., & Sun, H. (2019). Spatial effects of air pollution on public health in China. Environmental and Resource Economics, 73(1), 229-250. https://doi.org/ 10.1007/s10640-018-0258-4

[18] Bekkar, A., Hssina, B., Douzi, S., & Douzi, K. (2021). Air-pollution prediction in smart city, deep learning approach. Journal of Big Data, 8(1), 161. https://doi.org/10.1186/s40537-021-00548-1

[19] Anderson, J. O., Thundiyil, J. G., & Stolbach, A. (2012). Clearing the air: a review of the effects of particulate matter air pollution on human health. Journal of medical toxicology, 8(2), 166-175., https://doi.org/10.1007/s13181-011-0203-1

[20] Wakefield, S. E., Elliott, S. J., Cole, D. C., & Eyles, J. D. (2001). Environmental risk and (re) action: air quality, health, and civic involvement in an urban industrial neighbourhood. Health & Place, 7(3), 163-177. https://doi.org/10.1016/S1353-8292(01)00006-5

[21] Mabahwi, N. A. B., Leh, O. L. H., & Omar, D. (2014). Human health and wellbeing: Human health effect of air pollution. Procedia-Social and Behavioral Sciences, 153, 221-229. https://doi.org/10.1016/j.sbspro.2014.10.056

[22] Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: a review. Frontiers in Public Health, 8, 14. https://doi.org/10.3389/fpubh.2020.00014

[23] Mannucci, P. M., & Franchini, M. (2017). Health effects of ambient air pollution in developing countries. International Journal of Environmental Research and Public Health, 14(9), 1048. https://doi.org/10.3390/ijerph14091048

[24] Seiyaboh, E. I., & Izah, S. C. (2019). Impacts of soil pollution on air quality under Nigerian setting. Journal of Soil and Water Science, 3(1), 45-53. https://doi.org/10.36959/624/430

[25] Ileanwa, A. C., Atahchegbe, E. M., & Ekule, A. A. (2020). Impact of land pollution on the wellbeing of neighbourhoods in Minna, Nigeria. Central Asian Journal of Environmental Science and Technology Innovation, 3, 143-149. https://doi.org/10.22034/CAJESTI.2020.03.03

[26] Attademo, L., Bernardini, F., Garinella, R., & Compton, M. T. (2017). Environmental pollution and risk of psychotic disorders: A review of the science to date. Schizophrenia Research, 181, 55-59. https://doi.org/10.1016/j.schres.2016.10.003

[27] Serrano-Medina, A., Ugalde-Lizárraga, A., Bojorquez-Cuevas, M. S., Garnica-Ruiz, J., González-Corral, M. A., García-Ledezma, A., ... & Cornejo-Bravo, J. M. (2019). Neuropsychiatric disorders in farmers associated with organophosphorus pesticide exposure in a rural village of Northwest México. International Journal of Environmental Research and Public Health, 16(5), 689. https://doi.org/10.3390/ijerph16050689

[28] Gu, H., Yan, W., Elahi, E., & Cao, Y. (2020). Air pollution risks human mental health: an implication of two-stages least squares estimation of interaction effects. Environmental Science and Pollution Research, 27(2), 2036-2043. https://doi.org/10.1007/s11356-019-06612-x

[29] Pelgrims, I., Devleesschauwer, B., Guyot, M., Keune, H., Nawrot, T. S., Remmen, R., ... & De Clercq, E. M. (2021). Association between urban environment and mental health in Brussels, Belgium. BMC Public Health, 21(1), 635, 1-18. https://doi.org/10.1186/s12889-021-10557-7

[30] Xue, T., Zhu, T., Zheng, Y., & Zhang, Q. (2019). Declines in mental health associated with air pollution and temperature variability in China. Nature Communications, 10(1), 2165. https://doi.org/10.1038/s41467-019-10196-y

[31] Yang, Z., Song, Q., Li, J., Zhang, Y., Yuan, X. C., Wang, W., & Yu, Q. (2021). Air pollution and mental health: the moderator effect of health behaviors. Environmental Research Letters, 16(4), 044005.

[32] Wang, C., Feng, L., & Qi, Y. (2021). Explainable deep learning predictions for illness risk of mental disorders in Nanjing, China. Environmental Research, 202, 111740. https://doi.org/10.1016/j.envres.2021.111740

[33] Noël, C., Vanroelen, C., & Gadeyne, S. (2021). Qualitative research about public health risk perceptions on

ambient air pollution: A review study. SSM - Population Health, 15, 100879. https://doi.org/10.1016/j.ssmph.2021.100879

[34] Oltra, C., & Sala, R. (2014). A review of the social research on public perception and engagement practices in urban air pollution. Centro de Investigaciones Energeticas Medioambientales y Tecnologicas (CIEMAT), Madrid (Spain)

[35] Pinault, L., Thomson, E. M., Christidis, T., Colman, I., Tjepkema, M., van Donkelaar, A., Martin, R. V., Hystad, P., Shin, H., Crouse, D. L., & Burnett, R. T. (2020). The association between ambient air pollution concentrations and psychological distress. Health Reports, 31(7), 3–11. https://doi.org/10.25318/82-003-x202000700001-eng

[36] Bakolis, I., Hammoud, R., Stewart, R., Beevers, S., Dajnak, D., MacCrimmon, S., Broadbent, M., Pritchard, M., Shiode, N., Fecht, D., Gulliver, J., Hotopf, M., Hatch, S. L., & Mudway, I. S. (2021). Mental health consequences of urban air pollution: Prospective population-based longitudinal survey. Social Psychiatry and Psychiatric Epidemiology, 56(9), 1587–1599. https://doi.org/10.1007/s00127-020-01966-x

[37] Hautekiet, P., Saenen, N. D., Demarest, S., De Clercq, B., Lefebvre, W., Vanpoucke, C., & Nawrot, T. S. (2022). Air pollution in association with mental and self-rated health and the mediating effect of physical activity. Environmental Health, 21, 29. https://doi.org/10.1186/s12940-022-00839-x

[38] Aayush, K., Vishal, D., Hammad, N., & Manu, K. S. (2020). Application of artificial intelligence in curbing air pollution: The case of India. Journal of Advanced Research in Dynamical and Control Systems, 11(3), 285–290. https://doi.org/10.5958/2321-5763.2020.00044.X

[39] Usmani, R. S. A., Pillai, T. R., Hashem, I. A. T., Marjani, M., Shaharudin, R., & Latif, M. T. (2021). Air pollution and cardiorespiratory hospitalization, predictive modeling, and analysis using artificial intelligence techniques. Environmental Science and Pollution Research, 28(40), 56759–56771. https://doi.org/10.1007/s11356-021-14600-2

[40] Bekkar, A., Hssina, B., Douzi, S., & Douzi, K. (2021). Air-pollution prediction in smart city: Deep learning approach. Journal of Big Data, 8(1), 161. https://doi.org/10.1186/s40537-021-00548-1

[41] Guo, Q., Ren, M., Wu, S., Sun, Y., Wang, J., Wang, Q., & Chen, Y. (2022). Applications of artificial intelligence in the field of air pollution: A bibliometric analysis. Frontiers in Public Health, 10, 933665. https://doi.org/10.3389/fpubh.2022.933665

[42] Krupnova, T. G., Rakova, O. V., Bondarenko, K. A., & Tretyakova, V. D. (2022). Environmental justice and the use of artificial intelligence in urban air pollution monitoring. Big Data and Cognitive Computing, 6(3), 75. https://doi.org/10.3390/bdcc6030075

[43] Gupta, N. S., Mohta, Y., Heda, K., Armaan, R., Valarmathi, B., & Arulkumaran, G. (2023). Prediction of air quality index using machine learning techniques: A comparative analysis. Journal of Environmental and Public Health, 2023(1), 4916267. https://doi.org/10.1155/2023/4916267

[44] Bickerstaff, K., & Walker, G. (2001). Public understandings of air pollution: The 'localisation' of environmental risk. Global Environmental Change, 11(2), 133–145. https://doi.org/10.1016/S0959-3780(00)00063-7

[45] Coi, A., Minichilli, F., Bustaffa, E., Carone, S., Santoro, M., Bianchi, F., & Cori, L. (2016). Risk perception and access to environmental information in four areas in Italy affected by natural or anthropogenic pollution. Environment International, 95, 8–15. https://doi.org/10.1016/j.envint.2016.07.009

[46] Hameed, M., Shartooh, S., Zaher, S., & Yaseen, M. (2017). Application of artificial intelligence (AI) techniques in water quality index prediction: A case study in tropical region, Malaysia. Neural Computing and Applications, 28(S1), 893–905. https://doi.org/10.1007/s00521-016-2404-7

[47] Lucifora, C., Angelini, L., & Meteier, Q. (2021). Cyber-therapy: The use of artificial intelligence in psychological practice. In: Russo, D., Ahram, T., Karwowski, W., Di Bucchianico, G., Taiar, R. (eds) Intelligent Human Systems Integration 2021. IHSI 2021. Advances in Intelligent Systems and Computing, 1322. Springer, Cham. https://doi.org/10.1007/978-3-030-68017-6_19

[48] Gual-Montolio, P., Jaén, I., Martínez-Borba, V., Castilla, D., & Suso-Ribera, C. (2022). Using artificial intelligence to enhance ongoing psychological interventions for emotional problems in real or close to real time: A systematic review. International Journal of Environmental Research and Public Health, 19(13), 7737. https://doi.org/10.3390/ijerph19137737

[49] Kumar, A. (2021). Machine learning for psychological

disorder prediction in Indians during COVID-19 nationwide lockdown. Intelligent Decision Technologies, 15(1), 161–172. https://doi.org/10.3233/IDT-200077

[50] Sobus, J. R., DeWoskin, R. S., Tan, Y. M., Pleil, J. D., Phillips, M. B., George, B. J., Christensen, K., Schreinemachers, D. M., Williams, M. A., Hubal, E. A., & Edwards, S. W. (2015). Uses of NHANES biomarker data for chemical risk assessment: Trends, challenges, and opportunities. Environmental Health Perspectives, 123(10), 919–927. https://doi.org/10.1289/ehp.1409177

[51] Zhang, Y., Zhang, D., & Zhang, Z. (2023). A critical review on artificial intelligence-based microplastics imaging technology: Recent advances, hot-spots and challenges. International Journal of Environmental Research and Public Health, 20(2), 1150. https://doi.org/10.3390/ijerph20021150

[52] Delavar, M. R., Gholami, A., Shiran, G. R., Rashidi, Y., Nakhaeizadeh, G. R., Fedra, K., & Hatefi Afshar, S. (2019). A novel method for improving air pollution prediction based on machine learning approaches: A case study applied to the capital city of Tehran. ISPRS International Journal of Geo-Information, 8(2), 99. https://doi.org/10.3390/ijgi8020099

[53] Gupta, N. S., Mohta, Y., Heda, K., Armaan, R., Valarmathi, B., & Arulkumaran, G. (2023). Prediction of air quality index using machine learning techniques: A comparative analysis. Journal of Environmental and Public Health, 2023(1), 4916267. https://doi.org/10.1155/2023/4916267

[54] Josephine, G. M. R., Anitha, C. M., Padmaja, M., Lakshmi, V., Sreelatha, K., & Nagalakshmi, V. (2021). Water pollution: Psychological effect on human health & live reporting using IoT technology. Turkish Journal of Computer and Mathematics Education, 12(8), 2847–2852.https://turcomat.org/index.php/turkbilmat/article/view/4055

[55] Havugimana, E. R. N. E. S. T. E., Bhople, B. S., Kumar, A. N. I. L., Byiringiro, E. M. M. A. N. U. E. L., Mugabo, J. P., & Kumar, A. R. U. N. (2017). Soil pollution – major sources and types of soil pollutants. Environmental Science and Engineering, 11, 53–86.

[56] Münzel, T., Hahad, O., Daiber, A., & Landrigan, P. J. (2023). Soil and water pollution and human health: What should cardiologists worry about? Cardiovascular Research, 119(2), 440–449. https://doi.org/10.1093/cvr/cvac097

[57] Perveen, A., Taufiq, I., Hamzah, H. B., & Khan, R. bin A. W. (2015). Environmenta pollution's effects on human health and psychological wellbeing – A survey study. Asian Journal of Advanced Basic Sciences, 4(1), 52–56.

[58] Wright, S. L., & Kelly, F. J. (2017). Plastic and human health: A micro issue? Environmental Science & Technology, 51(12), 6634–6647. https://doi.org/10.1021/acs.est.7b00423

[59] Papadimou, S. G., Kantzou, O. D., Chartodiplomenou, M. A., & Golia, E. E. (2023). Urban soil pollution by heavy metals: Effect of the lockdown during the period of COVID-19 on pollutant levels over a five-year study. Soil Systems, 7(1), 28. https://doi.org/10.3390/soilsystems7010028

[60] Thushari, G. G. N., & Senevirathna, J. D. M. (2020). Plastic pollution in the marine environment. Heliyon, 6(8), e04709. https://doi.org/10.1016/j.heliyon.2020.e04709

[61] Akram, R., Natasha, Fahad, S., Hashmi, M. Z., Wahid, A., Adnan, M., Mubeen, M., Khan, N., Rehmani, M. I. A., Awais, M., Abbas, M., Shahzad, K., Ahmad, S., Hammad, H. M., & Nasim, W.(2019). Trends of electronic waste pollution and its impact on the global environment and ecosystem. Environmental Science and Pollution Research, 26(17), 16923–16938. https://doi.org/10.1007/s11356-019-04998-2

[62] Buralli, R. J., Ribeiro, H., Iglesias, V., Muñoz-Quezada, M. T., Leão, R. S., Marques, R. C., & Guimarães, J. R. D. (2020). Occupational exposure to pesticides and health symptoms among family farmers in Brazil. Revista de Saúde Pública, 54, 133. https://doi.org/10.11606/s1518-8787.2020054002263

[63] Cuthbertson, C. A., Newkirk, C., Ilardo, J., Loveridge, S., & Skidmore, M. (2016). Angry, scared, and unsure: Mental health consequences of contaminated water in Flint, Michigan. Journal of Urban Health, 93(6), 899–908. https://doi.org/10.1007/s11524-016-0089-y