





Article

Influence of Particulate Matter and Carbon Dioxide on Students' Emotions in a Smart Classroom

Gabriela Fretes ^{1,*}, Cèlia Llorba ¹, Ramon Palau ¹ and Joan Rosell-Llompart ^{2,3}

¹ Department of Pedagogy, University Rovira i Virgili, 43007 Tarragona, Spain; celia.llurba@urv.cat (C.L.); ramon.palau@urv.cat (R.P.)

² Chemical Engineering Department, University Rovira i Virgili, 43007 Tarragona, Spain; joan.rosell@urv.cat

³ Catalan Institution for Research and Advanced Studies—ICREA, 08010 Barcelona, Spain

* Correspondence: gabriela.fretes@estudiants.urv.cat

Abstract: The effects of air quality on health and cognition are well documented, but few studies have focused on its impact on emotions, leaving this area underexplored. This study investigates the influence of environmental factors—specifically particulate matter (PM₁, PM_{2.5}, and PM₁₀) and carbon dioxide (CO₂)—on students' basic emotions in secondary school classrooms. For the collection of environmental data, we used low-cost sensors, which were carefully calibrated to ensure acceptable accuracy for monitoring air quality variables, despite inherent precision limitations compared to traditional sensors. Emotions were recorded via camera and analyzed using a custom-developed code. Based on these data, we found significant but modest correlations, such as the negative correlation between PM levels and happiness, and positive correlations of CO₂ concentrations with fear and disgust. The regression models explained between 36% and 62% of the variance in emotions like neutrality, sadness, fear, and happiness, highlighting nonlinear relationships in some cases. These findings underscore the need for improved classroom environmental management, including the implementation of real-time air quality monitoring systems. Such systems would enable schools to mitigate the negative emotional effects of poor air quality, contributing to healthier and more conducive learning environments. Future research should explore the combined effects of multiple environmental factors to further understand their impact on student well-being.

Keywords: emotions; particulate matter; CO₂; secondary school; indoor air quality; classroom



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1. Introduction

Given that children spend many hours indoors at school, maintaining good indoor air quality (IAQ) is crucial for their educational experience. Numerous physical environmental factors may influence students' academic performance, but the indoor environmental quality of classrooms has been shown to significantly impact both teaching and learning outcomes [1]. Environmental factors, such as air quality, represent a direct influence on the teaching–learning process and offer significant opportunities for classroom innovation [2].

Studies on indoor environmental quality (IEQ) in schools frequently highlight common issues such as inadequate ventilation, improper temperatures, and the presence of airborne particles. Urban schools, in particular, face higher concentrations of particulate matter (PM) compared to rural schools, with 57% of urban respondents reporting the presence of particles in classrooms. These findings emphasize the widespread problem of poor air quality in educational settings and reinforce the need for improved ventilation, as current levels often fall below minimum recommended standards [3].

Ref. [4] further underscore the importance of addressing air quality in schools, noting that children are especially sensitive to pollutants such as VOCs, CO₂, NH₃, PM_{2.5}, and PM₁₀. Their study revealed that these factors often exceeded regulatory limits, making it clear that improved ventilation and air quality management are critical in educational settings.

In light of these challenges, this study takes an innovative approach by examining the impact of environmental factors—specifically particulate matter (PM₁, PM_{2.5}, and PM₁₀) and carbon dioxide (CO₂)—on students' emotions. Using low-cost sensors, which were carefully calibrated to ensure acceptable accuracy despite certain precision limitations, we monitored air quality levels in classrooms. This approach represents a first step towards affordable, scalable solutions for real-time air quality analysis, opening new pathways for research on how environmental conditions affect students' emotional well-being.

1.1. Particulate Matter and Carbon Dioxide

PM refers to a mixture of solid particles and liquid droplets suspended in the air, including dust, dirt, soot, smoke, and other aerosol particles. These particles are categorized based on their diameter, with PM_x (where x represents 10, 2.5, 1, or 0.1) indicating the mass of particles per unit volume of air with a diameter smaller than x micrometers. PM₁₀ particles, also known as inhalable particles, typically deposit in the thoracic or upper respiratory tract, while PM_{2.5} particles, referred to as fine inhalable particles, can penetrate deeper into the lungs, reaching the alveoli. Ultrafine particles, or PM_{0.1}, are smaller than 0.1 µm and pose unique health risks due to their ability to infiltrate both the lungs and the bloodstream, potentially leading to systemic health effects [5].

CO₂, accounting for approximately 0.04% of the atmosphere, is a prevalent gas composed of carbon and oxygen. In indoor environments, CO₂ levels are often used as indicators of ventilation quality, as elevated concentrations can signify inadequate airflow relative to the number of occupants. Insufficient ventilation can result in higher CO₂ levels, which, in turn, impact both comfort and cognitive function [6].

1.2. Importance of Monitoring and Regulation

Given the significant health risks associated with poor air quality, various health organizations have established strict guidelines to ensure safe indoor environments. The World Health Organization [7] recommends a PM_{2.5} limit of 10 µg/m³ as an annual mean, while a CO₂ concentration of 1000 ppm is considered the threshold for good IAQ. These standards are particularly important in educational settings, where students spend extended periods indoors and are more vulnerable to pollutants.

Ref. [8] provides further criteria for maintaining healthy and comfortable indoor environments in non-residential buildings. Table 1 summarizes the acceptable levels for CO₂ and temperature according to this standard:

Table 1. European standards for CO₂ and temperature (EN 16798-1:2019) [8].

Category	CO ₂ Concentration (Above Outdoor, ppm)	CO ₂ Concentration (Absolute Values, ppm)	Temperature (°C)
1st (High Quality)	550	1030	21–23
2nd (Moderate Quality)	800	1280	20–24
3rd (Low Quality)	1350	1830	19–25

This regulation classifies IAQ into three categories based on CO₂ concentration and temperature, ensuring that buildings meet acceptable health and comfort standards. Exceeding these levels can have significant health implications, particularly for students and staff, making it essential for schools to regularly monitor air quality and take appropriate actions to reduce exposure [9,10].

Technological advancements in environmental monitoring, particularly IoT-based systems and wearable sensors, have significantly improved the ability to track IAQ in real time. These technologies allow for schools not only to ensure compliance with health standards but also to create dynamic environments that can quickly respond to changes in air quality. For example, a study conducted at a K-12 school in Melbourne demonstrated how these systems can monitor CO₂, PM, temperature, and humidity levels, providing

insights into how indoor climate affects students' emotions, engagement, and overall well-being [11].

In line with these developments, the study [12] recommends the widespread adoption of IAQ sensors in schools. These sensors, compliant with the UL 2905 standard [13], monitor key parameters such as PM₁, PM_{2.5}, CO₂, temperature, humidity, and total volatile organic compounds (TVOCs). However, despite these advancements, [14] found that CO₂ levels in classrooms often exceed recommended limits, sometimes reaching as high as 4000 ppm due to insufficient ventilation. This highlights the ongoing need for better ventilation management to prevent discomfort and health risks associated with poor air quality.

1.3. Health Effects

While this study focuses on the emotional impacts of air quality, it is important to acknowledge the strong connection between physical health and emotional well-being. Poor air quality, characterized by high levels of PM and CO₂, affects not only respiratory and cardiovascular health but also contributes to emotional distress, particularly in children, a vulnerable population [15,16].

Exposure to PM_{2.5} has been linked to systemic health effects that extend beyond the respiratory system, influencing cognitive function and emotional stability [6]. Similarly, high CO₂ levels—often exceeding 4000 ppm due to poor ventilation—cause discomfort and respiratory problems, which can lead to heightened stress and emotional instability [14].

Improving ventilation has shown direct benefits for both physical health and emotional well-being. Better ventilation reduces headaches, fatigue, and discomfort, creating a more supportive environment for students' emotional health [17]. Additionally, increased ventilation rates reduce illness-related absences, further highlighting the importance of maintaining good air quality for both physical and emotional health [18].

1.4. Cognitive Effects

Numerous studies have shown a clear correlation between poor IAQ and diminished cognitive performance, particularly in tasks that require focus and problem-solving. High CO₂ concentrations, along with insufficient ventilation, have been linked to reduced cognitive function and lower academic scores, particularly in subjects like mathematics [19,20]. For instance, in classrooms where CO₂ levels reached 2714 ppm—well above the recommended 1500 ppm—students reported discomfort, which negatively impacted their performance, with effectiveness falling between 48% and 62% [20].

In addition to these findings, there is a moderate correlation between CO₂ concentration and student well-being during the learning process. Although the relationship is not definitive, elevated CO₂ levels and poor ventilation have been shown to affect students' ability to concentrate and perform academically, particularly in problem-solving tasks like mathematics [19,21].

Furthermore, studies indicate that higher levels of PM_{2.5} and CO₂ are associated with slower response times and lower accuracy in cognitive tasks such as the Stroop test and arithmetic [22]. Reducing CO₂ concentrations from 2100 ppm to 900 ppm, for example, has been shown to improve test performance by 12% in terms of speed and 2% in terms of accuracy, while also increasing daily attendance by 2.5% [23]. These findings underscore the clear benefits of improving ventilation in classrooms to enhance both cognitive performance and attendance.

1.5. Effects on Emotions and Mental Health

The emotional impact of air pollutants such as CO₂ and PM has been less documented, with varying effects depending on the type of pollutant and environmental conditions. Exposure to high levels of CO₂ has been shown to trigger emotional responses resembling panic attacks. According to [24], inhaling elevated levels of CO₂ can replicate the fear and discomfort typical of spontaneous panic episodes. This suggests that poor IAQ,

particularly in enclosed spaces like classrooms, can have profound emotional consequences for occupants.

In terms of PM, research has demonstrated that PM_{2.5} is particularly harmful to emotional well-being. Ref. [25] observed that in Beijing, negative emotional responses increased when PM_{2.5} levels reached approximately 150 AQI, a level classified as “unhealthy”. Furthermore, different social groups exhibited varying sensitivities to emotional well-being, with more pronounced negative emotions occurring when AQI levels surpassed 200, classified as “very unhealthy”. Similarly, Ref. [26] found a significant link between elevated PM_{2.5} levels and emotional intensity, as evidenced by an increase in negative social media posts during periods of high pollution. These findings underscore how poor air quality can heighten negative emotions in urban environments, particularly under severe pollution conditions.

Regarding PM₁₀, Ref. [27] noted that during the winter, higher levels of PM₁₀ contributed to a rise in negative public sentiment, reflected in media coverage. This research highlights how air pollution can shape not only individual emotions but also collective public perception, with pollution reduction efforts leading to more positive emotions and public perceptions.

General air pollution, encompassing a range of contaminants like PM and nitrogen dioxide (NO₂), has also been linked to significant emotional and mental health impacts. Ref. [28] revealed a strong association between short-term exposure to urban air pollutants and an increase in emergency visits for mental health issues among youth aged 8 to 24. This suggests that younger populations are particularly vulnerable to the emotional and psychological consequences of air pollution.

One study [29] introduced the concept of Affective Sensitivity to Air Pollution (ASAP), which measures emotional fluctuations in response to daily changes in air pollution. Individuals with higher ASAP experience more pronounced emotional changes when pollution levels shift. This construct emphasizes the variability in how individuals emotionally react to pollution, suggesting that sensitivity to air quality can significantly affect emotional well-being.

Emotional states themselves can also modulate the effects of air pollution. Ref. [30] demonstrated that individuals with lower emotional well-being, such as those experiencing unhappiness, are more vulnerable to the negative effects of air pollution on physical health, particularly in lung function and blood pressure. In contrast, happier individuals showed less pronounced adverse effects, highlighting the interplay between emotional health and environmental stressors.

Finally, classroom environmental conditions play a crucial role in shaping students' emotional engagement and overall well-being. Ref. [31] found that temperature, air enthalpy, and humidity significantly affected students' vigor and dedication to their studies. Higher temperatures were linked to reduced energy and concentration, while increased air enthalpy and humidity were positively associated with dedication and vigor. Additionally, elevated levels of total volatile organic compounds (TVOCs) were associated with diminished dedication, suggesting that poor IAQ can impair emotional and cognitive engagement in educational settings.

Although a substantial body of research has explored the impact of poor indoor environmental quality on cognitive function and overall health, studies focusing on the emotional effects remain relatively scarce. Much of the existing literature highlights the link between exposure to pollutants such as CO₂ and PM with cognitive decline and physical health issues, particularly in educational settings. However, the emotional dimension has been less thoroughly examined, despite its critical importance in the context of student well-being and learning outcomes.

This study seeks to address this gap by exploring the relationship between environmental factors, specifically PM, CO₂ levels, and the basic emotions of students. By focusing on how these pollutants affect emotional states, we aim to provide a more comprehensive understanding of the indoor environmental quality in classrooms. Our approach is

innovative in that it shifts the focus from traditional cognitive and health-based impacts to emotional well-being, offering new insights into how air quality affects students on a psychological and emotional level.

2. Materials and Methods

2.1. Participants

In this study, 76 students from a secondary school in an urban area of northeastern Spain participated. The age of the students ranged from 12 to 18 years old, so students were attending at different levels. Precisely, two student groups belonged to the first year of secondary school, one group to the fourth year, two groups to the first year of upper secondary school, and one student group to the second year of upper secondary school. The number of participating students per classroom was 24, with a range of 12 to 32 students per class. Groups are divided equally by gender. There were 3 teachers involved in the present study, all of them female.

2.2. Type of Study

An exploratory observational and correlational design was conducted to gather environmental data, including CO₂ and PM levels, as well as emotional responses from students across six different class groups in a secondary school. Environmental conditions were neither manipulated nor experimentally controlled, allowing for data collection under authentic, real-world conditions. While this approach limits causal inference regarding the observed associations, specific measures were taken to minimize variability. In particular, we focused on teacher-led sessions and considered factors such as group similarity and gender distribution. These steps enhance the reliability of the observations, although they do not fully eliminate the potential influence of external variables.

2.3. Experimental Procedure

This study was conducted over four weeks during the first term of the school year. The procedure involved the simultaneous collection of environmental data and students' emotions during their regular class sessions. Technology and also another technology-related subject, called SDG Project (Sustainable Development Goals—Green Project), were the subjects that students were learning about during this study. The following steps were followed:

- **Classroom setting:** The environmental monitoring kit was placed in the classroom, strategically positioned near the entrance to measure key environmental parameters, including CO₂ concentration and PM (PM₁, PM_{2.5}, and PM₁₀). The device recorded data every 10 min throughout the school day.
- **Emotion data collection:** During class sessions, a laptop equipped with a camera was used to capture students' facial expressions. The camera was positioned to cover as many students as possible within its field of view. Videos were recorded and later processed using a custom Python version 3.11.1 code to detect faces and analyze emotions through the Python Facial Expression Analysis Toolbox (Py-Feat) version 0.3.4.
- **Data synchronization:** Environmental data from the ACTUA-096 kit and emotion data from the facial recognition system were synchronized and stored in a database. This allowed for the analysis of the relationship between environmental conditions and students' emotions.
- **Data analysis:** The collected data were then analyzed to identify correlations between the environmental factors and students' emotions, and to develop regression models that could predict emotional responses based on the environmental variables.

2.4. Emotion Recognition Data Collection

First of all, we developed a code capable of detecting and identifying faces and also analyzing facial expressions by a laptop camera. Python 3.11.1 was used as the programming

environment in which the code for detection, identification, and recognition of emotions from faces was developed. Then, Py-Feat was the chosen tool (Computational Social Affective Neuroscience Laboratory (COSAN Lab) at Dartmouth College, Hanover, NH, USA) to obtain the emotions of the attending class's students and used to promptly process, analyze, and visualize the facial expression data. After that, the data were transferred into a database for further analysis, also establishing the first approximations to the relationship between students' emotions and other conditions such as the classroom environmental data [32,33].

The laptop camera pointed at and recorded the students, allowing for data acquisition. It covered as many students as were in the field of view of the webcam. The camera could bring both the front of the class and the back of the class into clear focus, although the students had to look straight ahead to be detected. The lessons were recorded, and the videos were uploaded and stored digitally. In turn, the videos were split every 10 s into consecutive frames; this was made possible by our personalized code, converting the images into png files for subsequent data analysis. Finally, a csv file was extracted with all the emotions collected from the students detected in the image. Once the files with all the emotion data were obtained, all the images were deleted.

2.5. Environmental Kit Data Collection

To obtain environmental data for the present study, a custom-designed device was used. It is labeled ACTUA-096 kit and belongs to the ACTUA Project [34]. The project was started during the COVID-19 pandemic in May 2021. The project applies technology and data analysis to investigate the transmission of respiratory viruses, such as SARS-CoV-2, the virus causing COVID-19, in school classrooms. Identical devices to the ACTUA-096 kit (Universitat Rovira i Virgili (URV), Tarragona, Spain) were mainly placed in kindergarten and elementary school classrooms, but in our case, the device was placed in a secondary school as well. This project also includes the development of a monitoring tool that tracks various contextual variables, as well as a data analysis infrastructure to process the collected information.

The environmental monitoring kit (Figure 1) is a $20 \times 20 \times 10$ cm box enclosed by a wooden base and perforated sheet, which contains a single-board computer, a Raspberry Pi, and a range of sensors that capture the contextual variables of this study, among others to measure CO₂ concentration and PM. These sensors are connected to the Raspberry Pi through cables inside the kit itself [34]. The specific relevant sensors for the present study are a Sensirion SCD30 (Sensirion AG, Stäfa, Switzerland) for the CO₂ concentration, and a Plantower PMS5003 (Shenzhen Planck Technology Co., Ltd. (Plantower), Shenzhen, China) for the PM. The SCD30 is a calibrated and linearized sensor module that uses NDIR technology for detecting CO₂. The PMS5003 is a particle concentration sensor based on laser-scattering of the airborne particles, from which equivalent particle diameter and the number of particles within size ranges per unit volume are calculated in situ based on MIE theory. Each environmental kit in the ACTUA Project (over 130 kits) was tested after assembly under different ambient conditions by comparing the outputs from the sensors of our kit to those of a reference kit that had previously been tested extensively against factory-calibrated instruments. The temperature and humidity outputs from the SCD30 sensor of the reference kit were compared against those from a Vaisala HM41 m (Vaisala Oyj, Vantaa, Finland), while its CO₂ values against those of a Vaisala GM70 carbon dioxide meter with a GMP222 probe (Vaisala Oyj, Vantaa, Finland) (with VSL traceable calibration). The PM_x values of the reference kit from the PMS5003 sensor were compared against those obtained with a TSI AeroTrak 9306 (TSI Incorporated, Shoreview, MN, USA) optical particle counter (with NIST traceable calibration). More than 130 kits were tested in this way in the ACTUA Project, including the kit used in this study (096).

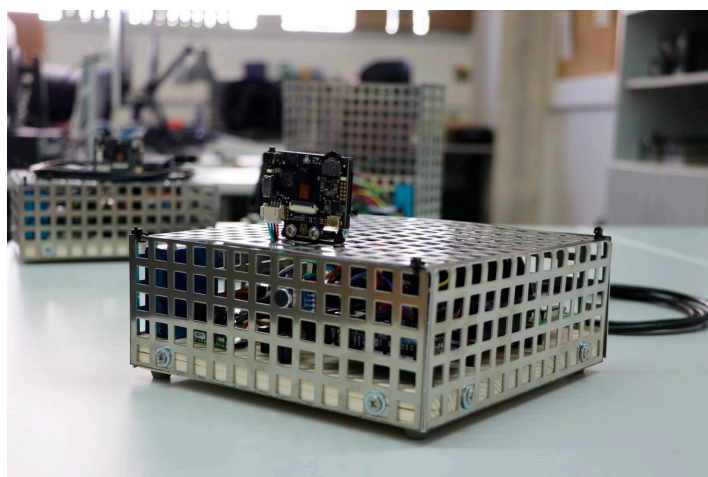


Figure 1. ACTUA Kit device for environmental factors monitoring.

To control the parameters and monitor the environmental parameters as efficiently as possible, the kit was placed at a strategic point, near the classroom entrance door to be able to connect it to an external sensor that detects whether the door is open or closed. See Table 2 for the technical specifications and precision of the sensors.

Table 2. Technical specifications of environmental sensors ^a.

Sensor	Manufacturer	Variable	Unit	Accuracy
SCD30	Sensirion (Stäfa, Switzerland)	Temperature	°C	$\pm(0.4\text{ °C} + 0.023 \times (T\text{ [°C]} - 25\text{°C}))$
SCD30	Sensirion	Concentration of carbon dioxide	ppm	$\pm(30\text{ ppm} + 3\% \text{ MV})^b$
PMS5003	Plantower (Shenzhen, China)	Concentration of PM (PM ₁ , PM _{2.5} , PM ₁₀)	$\mu\text{g}/\text{m}^3$	$\pm 10\%$ between 100–500 $\mu\text{g}/\text{m}^3$

Adapted from [35] Copyright 2023, the authors. ^a Extracted from the manufacturer datasheet. ^b Accuracy in the range 400–10,000 ppm. MV means measured value.

The kit measures every 10 min a range of variables to monitor conditions inside the classroom, such as temperature, ambient humidity, CO₂ concentration, and various PM concentrations, among others. To measure classroom conditions (see Table 2), the ACTUA Project has developed an IoT-based contextual variable monitoring platform that facilitates the achievement and deployment of sensory systems with network connectivity capabilities. This device sends data collected every 8 h to the ACTUA Project server via the Internet. The server stores all the information in a single database and provides a web application capable of managing and visualizing all the system data.

2.6. Data Analysis

This study was conducted in a natural classroom setting where environmental changes occurred naturally without experimental manipulation, capturing real classroom conditions. After excluding missing data, 29,137 valid records were obtained for every type of PM and 24,732 for CO₂, ensuring data quality and consistency in the analysis.

The choice of a 10 min interval for measuring indoor parameters aligns with prior research in similar contexts. Studies such as [36] highlighted that a 10 min interval is optimal for capturing periodic variations in indoor temperature while avoiding an excess of data that could complicate analysis without adding significant value. Similarly, [37] used a 10 min interval to analyze thermal comfort and indoor air quality in an educational center, and [38] employed 15 min intervals to monitor environmental parameters in residential buildings, ensuring frequent updates. These methodological decisions demonstrate that

a 10 min interval is sufficient to capture significant changes in parameters of interest, especially in a controlled environment like a classroom.

In contrast, emotion recognition requires a more detailed temporal approach due to the dynamic and rapidly changing nature of emotions. Emotional data were recorded every 10 s, an interval that captured quick and subtle changes in emotional expressions, providing high temporal resolution suitable for analyzing the relationship between emotions and environmental factors. While studies such as [39] used one-minute intervals, the choice of a 10 s interval reflects the need to more accurately capture emotional fluctuations.

To address the asynchrony between environmental and emotional data, the forward fill technique was adopted. This choice is grounded in the need to seamlessly fill temporal gaps in environmental data by leveraging the most recent available information. Employing this technique allows for maintaining a continuous and uniform temporal sequence, thereby facilitating the joint analysis of environmental and emotional data without compromising temporal coherence. Furthermore, aligning the data in this manner provides a solid foundation for investigating potential relationships between environmental factors and recorded emotions.

In addition, correlation and regression analyses were conducted to explore the relationships between environmental factors and emotional responses. To capture potential nonlinear associations, it was necessary to transform the variables into quadratic terms. This decision was motivated by the recognition that linear relationships may not fully capture the complexity of interactions between environmental variables and emotional states. By including quadratic terms, we aimed to account for potential curvature in the relationships, allowing for a more comprehensive analysis of the data and yielding insights into the nuanced dynamics between environmental factors and emotions.

The graphics were created using Python with the libraries matplotlib and seaborn.

3. Results

This section explores the relationships between environmental factors, including PM_1 , $PM_{2.5}$, PM_{10} , and CO_2 , and students' emotions (anger, disgust, fear, happiness, sadness, surprise, and neutral). The analysis begins with Spearman's correlations between each environmental factor and emotions are examined. Following this, linear regression models are developed for each emotion. A general summary of the models is provided to facilitate the understanding of key findings.

To provide an overview of the relationships between the environmental factors and emotions, a heatmap is presented (Figure 2). This heatmap summarizes the strength and direction of the correlations, using warmer colors to indicate positive correlations and cooler colors for negative correlations. The significance levels are marked (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$), highlighting the robustness of these associations.

The variables PM_1 , $PM_{2.5}$, and PM_{10} exhibited high and positive correlations among themselves, all with significant Spearman correlation coefficients ($p < 0.001$), suggesting a strong relationship between these particles. Additionally, a significant negative correlation is observed between PM_1 , $PM_{2.5}$, and PM_{10} with CO_2 ($p < 0.001$), indicating an inverse relationship.

Various correlations between emotions and environmental variables were observed in this study. Regarding PM, some significant and weak associations with emotions were found. For instance, PM_1 showed a significant and negative correlation with surprise. $PM_{2.5}$ showed a significant and negative correlation with surprise ($\rho = -0.03$, $p \leq 0.001$) and positive with happiness ($\rho = 0.03$, $p < 0.001$), while PM_{10} exhibited correlations with surprise ($\rho = -0.04$, $p < 0.001$) and anger ($\rho = 0.03$, $p \leq 0.001$).

Furthermore, the concentration of CO_2 showed stronger correlations with various emotions. Positive associations were found between CO_2 and emotions such as anger ($\rho = 0.098$, $p < 0.001$) and disgust ($\rho = 0.078$, $p < 0.001$), and negative associations with sadness ($\rho = -0.051$, $p < 0.001$) and fear ($\rho = -0.031$, $p < 0.001$).

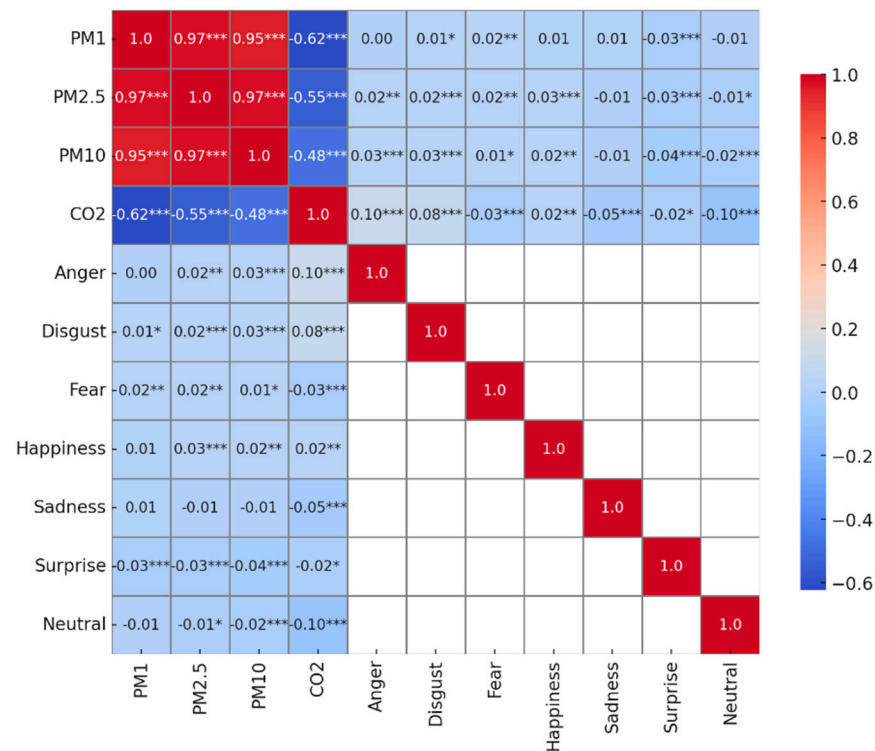


Figure 2. Spearman’s correlations among environmental factors (PM and CO₂) and emotions with significance levels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Building on the correlations observed, we further examined the predictive power of the environmental variables using regression models. Table 3 provides a summary of these models, highlighting the efficacy of CO₂, PM₁, PM_{2.5}, and PM₁₀ in predicting basic emotions. This analysis offers insight into how these environmental factors influence emotions, beyond the correlation analysis.

Table 3. Summary of regression analyses for basic emotions.

Model M ₁ ¹	R	R ²	Adjusted R ²	RMSE	R ² Change	df1	df2	p	Durbin–Watson		
									Autocorrelation	Statistic	p
Anger	0.014	0.000	−0.000	2.373×10^7	0.000	7	24,435	0.661	-2.045×10^{-4}	2.000	0.995
Disgust	0.270	0.073	0.072	0.056	0.073	7	24,450	<0.001	0.020	1.960	0.001
Fear	0.742	0.551	0.551	0.118	0.551	7	24,449	<0.001	0.075	1.849	<0.001
Happiness	0.603	0.364	0.364	0.159	0.364	7	24,450	<0.001	0.042	1.917	<0.001
Sadness	0.734	0.538	0.538	0.151	0.538	7	24,450	<0.001	0.116	1.769	<0.001
Surprise	0.701	0.491	0.491	0.204	0.491	7	24,450	<0.001	0.072	1.857	<0.001
Neutral	0.789	0.622	0.622	0.198	0.622	7	24,450	<0.001	0.068	1.865	<0.001

¹ M₁ includes PM₁, PM_{2.5}, PM₁₀, CO₂, sq_PM₁, sq_PM_{2.5}, sq_PM₁₀, and sq_CO₂.

The models for neutral, fear, sadness, surprise, and happiness emotions showed substantial R² values, ranging from 0.364 for happiness to 0.622 for neutral, indicating that a significant proportion of variance in these emotions is explained by the predictors used in the models. All models, except for anger (R² = 0.000), are statistically significant with p-values less than 0.001, supporting the robustness of the models. The Durbin–Watson statistics for all models are close to 2, suggesting no significant autocorrelation in the residuals, ensuring the reliability of the regression estimates.

To visually summarize these findings, Figure 3 presents the explained variance (R^2) and predictive accuracy (RMSE) for each emotion.

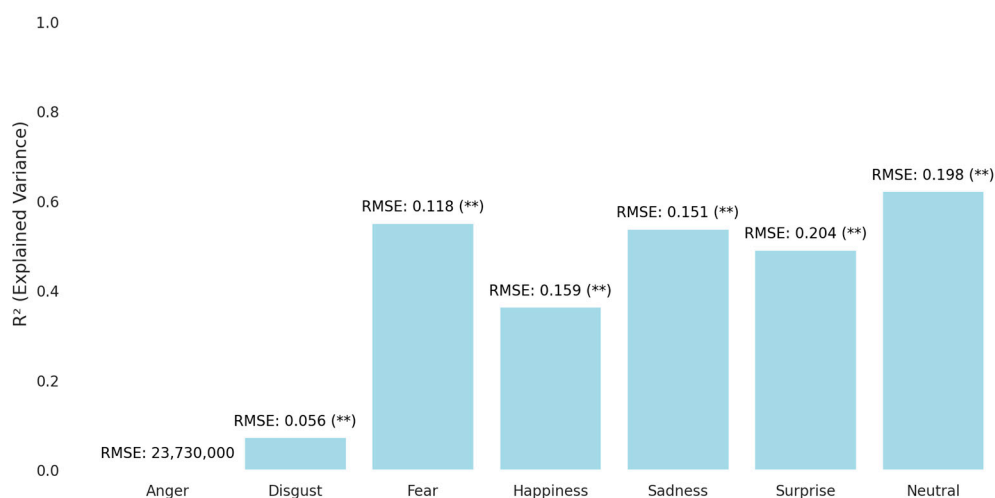


Figure 3. Explained variance (R^2) and predictive accuracy (RMSE) for emotions based on environmental factors. ** Statistically significant at $p < 0.001$.

The neutral emotion model was the most robust in terms of explained variance, with an R^2 of 0.622, indicating that over 62% of the variance in this emotion was explained by the environmental factors analyzed. Additionally, the root mean square error (RMSE = 0.198) suggested notable accuracy in the predictions, further supported by a highly significant p -value ($p < 0.001$).

The fear model showed strong results, with an R^2 of 0.551, explaining more than 55% of the variance in fear, with an RMSE of 0.118. The p -value (< 0.001) indicated the high reliability of the model's predictions.

Similarly, the sadness model exhibited an R^2 of 0.538, explaining over 53% of the variance in this emotion. The RMSE was 0.151, and the model was statistically significant ($p < 0.001$), making it a reliable predictor of sadness.

The surprise model explained 49% of the variance ($R^2 = 0.491$), with an RMSE of 0.204. It was statistically significant ($p < 0.001$), though slightly less predictive compared to the sadness and fear models.

For happiness, the model explained 36% of the variance ($R^2 = 0.364$) with an RMSE of 0.159. The model was also statistically significant ($p < 0.001$), though it explained a smaller proportion of variance relative to the other emotions.

The disgust model had a lower R^2 of 0.073, indicating that only 7.3% of the variance in disgust could be attributed to the environmental factors. The RMSE was 0.056, and although the model was statistically significant ($p < 0.001$), it was less effective in predicting this emotion.

Lastly, the anger model was ineffective, with an R^2 of 0.000 and an adjusted R^2 of -0.000 . The RMSE was extremely high, and the model did not reach statistical significance ($p = 0.661$), suggesting that the environmental predictors did not explain variance in anger.

This section analyzes how environmental factors influence students' emotions. The standardized regression showed the impact of PM and CO₂, both directly and in quadratic effects, on students' emotions. Table 4 summarizes the regression coefficients and their effects.

In this analysis, the largest effects of each variable are highlighted:

PM₁ and its quadratic term (sq_PM₁) have significant nonlinear effects on emotions like happiness and surprise. Negative coefficients in the linear term and positive coefficients in the quadratic term suggest a U-shaped relationship. Initially, these emotions decrease with increasing PM₁ levels, but then increase at higher levels. For example, for happiness, the linear coefficient is negative ($\beta = -0.954$, $p < 0.001$) and the quadratic coefficient is

positive ($\beta = 0.552, p < 0.001$). Similarly, for surprise, the linear coefficient is $\beta = -0.705$ ($p < 0.001$) and the quadratic coefficient is $\beta = 0.496$ ($p < 0.001$).

Table 4. Comparison of standardized regression coefficients across emotions.

Predictor	Disgust	Fear	Happiness	Sadness	Surprise	Neutral
PM ₁	−0.166 (0.033)	−0.195 (0.013)	−0.954 (<0.001)	0.961 (<0.001)	−0.705 (<0.001)	−0.220 (0.004)
PM _{2.5}	−0.075 (0.461)	0.455 (<0.001)	1.102 (<0.001)	−0.620 (<0.001)	0.483 (<0.001)	0.128 (0.206)
PM ₁₀	0.091 (0.207)	−0.092 (0.207)	0.012 (0.869)	−0.031 (0.664)	0.337 (<0.001)	0.858 (<0.001)
sq_PM ₁	0.182 (0.007)	0.224 (0.001)	0.552 (<0.001)	−0.636 (<0.001)	0.496 (<0.001)	0.197 (0.003)
sq_PM _{2.5}	−0.101 (0.239)	−0.473 (<0.001)	−0.750 (<0.001)	0.298 (<0.001)	−0.256 (0.003)	0.421 (<0.001)
sq_PM ₁₀	0.083 (0.231)	0.112 (0.108)	0.074 (0.280)	0.095 (0.172)	−0.374 (<0.001)	−1.364 (<0.001)
CO ₂	0.048 (<0.001)	0.115 (<0.001)	0.007 (0.180)	0.152 (<0.001)	0.075 (<0.001)	0.029 (<0.001)

For sadness, the pattern was opposite, with a positive coefficient on the linear term ($\beta = 0.961, p < 0.001$) and negative on the quadratic term ($\beta = -0.636, p < 0.001$), indicating that sadness increases with initial increases in PM₁, but decreases at higher levels of exposure.

The analyses for PM_{2.5} and its quadratic term (sq_PM_{2.5}) show significant effects on several emotions. With fear ($\beta = 0.455, p < 0.001$) and happiness ($\beta = 1.102, p < 0.001$), positive coefficients were observed in the linear term, indicating that higher levels of PM_{2.5} are associated with an increase in these emotions. However, the quadratic term showed significant negative effects on both emotions (fear: $\beta = -0.473, p < 0.001$; happiness: $\beta = -0.750, p < 0.001$), suggesting a nonlinear inverted U-shaped relationship.

For sadness, a significant negative coefficient was found in the linear term ($\beta = -0.620, p < 0.001$), with a positive quadratic coefficient ($\beta = 0.298, p < 0.001$), indicating a U-shaped behavior, where sadness decreases with initial increases in PM_{2.5}, but increases at higher levels of exposure. Similarly, surprise showed U-shaped behavior, with a positive coefficient on the linear term ($\beta = 0.483, p < 0.001$) and a negative quadratic coefficient ($\beta = -0.256, p = 0.003$).

Finally, neutral presented a positive quadratic coefficient ($\beta = 0.421, p < 0.001$), suggesting a nonlinear relationship, although no significant effects were found in the linear term ($p = 0.206$).

The analysis of the effects of PM₁₀ and its quadratic term (sq_PM₁₀) on emotions showed some significant results on surprise and neutral emotions.

For the linear term of PM₁₀, a significant positive coefficient was observed in surprise ($\beta = 0.337, p < 0.001$) and neutral ($\beta = 0.858, p < 0.001$), suggesting that higher levels of PM₁₀ are associated with an increase in these emotions. The quadratic term (sq_PM₁₀) also showed significant effects in surprise ($\beta = -0.374, p < 0.001$) and neutral ($\beta = -1.364, p < 0.001$), indicating a nonlinear relationship, with a decrease in these emotions at higher PM₁₀ levels.

For disgust, fear, sadness, surprise, and neutral, CO₂ has a positive and significant impact. Specifically, in disgust ($\beta = 0.048, p < 0.001$), fear ($\beta = 0.115, p < 0.001$), sadness ($\beta = 0.152, p < 0.001$), surprise ($\beta = 0.075, p < 0.001$), and neutral ($\beta = 0.029, p < 0.001$), an increase in CO₂ levels is associated with an increase in these emotions. No significant effects were found in happiness ($p = 0.180$).

To better visualize the effects of each environmental variable on emotions, Figure 4 presents the standardized regression coefficients.

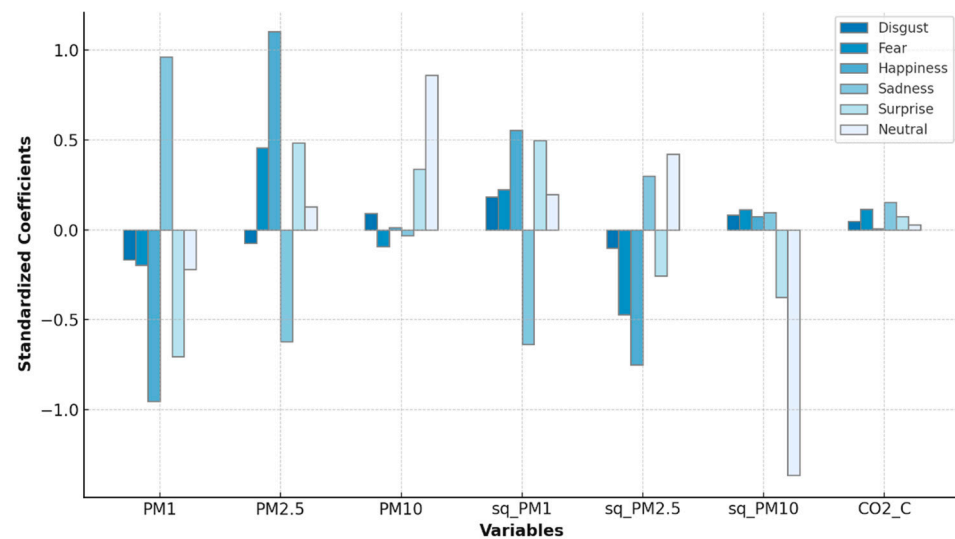


Figure 4. Standardized regression coefficients for each emotion.

4. Discussion

The aim of this study was to explore the impact of environmental factors, specifically CO₂ and PM, on students' emotions in classroom. Previous research suggested that air quality can significantly affect cognitive, health, and emotion dimensions, with poorer air quality often linked to health problems, less performance, and negative affect. By using regression models and correlation analyses, our study quantify the influence of various pollutants, including PM₁, PM_{2.5}, PM₁₀, and CO₂, on emotions such as anger, fear, sadness, happiness, disgust, and neutral.

The results revealed significant but weak correlations between levels of CO₂ and various emotions, particularly those with negative connotations. Positive associations were found between CO₂ and emotions such as anger ($\rho = 0.098, p < 0.001$), disgust ($\rho = 0.078, p < 0.001$), and sadness ($\rho = -0.051, p < 0.001$). These correlations suggest that higher levels of CO₂ may be associated with an increase in negative emotions. These findings are partially consistent with previous research, particularly regarding the link between CO₂ and negative emotions. Although there was no positive Spearman correlation between CO₂ and fear, the regression model coefficient did reveal a small but significant coefficient with fear. This supports the idea that an increase in CO₂ could be related to a rise in fear levels, which is consistent with the literature [24].

Beyond the effects of CO₂, our study also revealed significant associations between PM and various emotions. For example, PM_{2.5} showed a weak but significant correlation with emotions such as anger ($\rho = 0.016, p = 0.006$), disgust ($\rho = 0.023, p < 0.001$), and fear ($\rho = 0.017, p = 0.003$), while PM₁₀ was similarly associated with disgust ($\rho = 0.029, p < 0.001$) and fear ($\rho = 0.014, p = 0.015$).

These findings align with the existing literature indicating the significant impact of indoor PM, particularly PM_{2.5}, on emotional well-being. Studies such as [25,26] demonstrated that increases in PM_{2.5} levels are correlated with negative emotional responses, such as those observed in social media posts. Similarly, Ref. [27] analysis of PM₁₀ highlighted a relationship between increased PM levels and negative public sentiment, supporting our findings.

In addition, Ref. [30] research emphasizes how emotional health can modulate the effects of air pollution, showing that individuals who are less happy are more vulnerable to its adverse impacts. This may explain the variability in emotional responses to environ-

mental factors observed in our study, where more negative emotions were correlated with higher particulate matter levels.

Regarding the regression models, we observed a pattern in neutral emotion. The initial increase in PM₁₀ raises the likelihood of neutral emotion, potentially indicating a decrease in the intensity or frequency of other emotions. Neutral emotion may prevail when other basic emotions are not expressed. Although this observation is not definitive, it suggests that higher particulate matter levels could reduce the cognitive and emotional arousal necessary to trigger stronger emotional reactions. This aligns with previous studies that have shown poor air quality, particularly elevated PM and CO₂ levels, to be associated with reduced cognitive performance and emotional engagement [19–21]. As cognitive and emotional responses diminish, neutral emotional states might become more prevalent. However, further research is needed to fully explore the mechanisms behind this relationship.

The regression analysis for sadness revealed a positive relationship with PM₁ levels, with a linear coefficient of 0.961 ($p < 0.001$), indicating that higher PM₁ levels are initially associated with increased feelings of sadness. The negative quadratic coefficient of -0.636 ($p < 0.001$) suggests a decrease in sadness at higher PM₁ levels, highlighting a nonlinear relationship. This pattern points to an inverted U-shaped curve, where sadness increases with initial increases in PM₁ but begins to decrease as PM₁ levels continue to rise. While the literature does not specifically address PM₁, our findings are consistent with general research linking particulate matter to negative emotional responses [25–27], including an increase in mental health emergency visits among young people [28].

In addition to sadness, other emotions such as happiness and surprise also exhibited significant nonlinear relationships with PM₁ levels. For happiness, we found a negative linear coefficient ($\beta = -0.954$, $p < 0.001$) and a positive quadratic coefficient ($\beta = 0.552$, $p < 0.001$), indicating a U-shaped relationship. This suggests that happiness decreases with initial increases in PM₁ but begins to rise again at higher levels of exposure. Similarly, surprise showed a negative linear coefficient ($\beta = -0.705$, $p < 0.001$) and a positive quadratic coefficient ($\beta = 0.496$, $p < 0.001$), reflecting a comparable pattern. These findings imply that the impact of PM₁ on emotional responses is complex and varies across different emotions, necessitating further investigation to understand the underlying mechanisms.

Overall, our findings suggest that poor air quality is associated with negative emotional responses. However, more research is necessary to fully understand the nuances of how fluctuations in air quality affect emotions. Constructs like Affective Sensitivity to Air Pollution (ASAP) [29], offer promising frameworks for further exploration of how individual sensitivity to air quality impacts emotional well-being.

In addition to the emotional effects, it is important to acknowledge the well-documented cognitive and health impacts of poor air quality. Elevated levels of CO₂ and particulate matter (PM) have been shown to reduce cognitive performance, particularly in tasks requiring concentration and problem-solving [19,20]. This cognitive decline may also influence emotions, as lower cognitive function can lead to frustration, stress, and disengagement in learning environments.

Furthermore, poor IAQ is associated with adverse health outcomes [14]. These health problems can exacerbate emotional distress, particularly in children. The overlap between cognitive, physical, and emotional effects highlights the importance of addressing air quality comprehensively in educational settings.

5. Conclusions

This study provides significant evidence of the relationship between environmental variables and emotions in educational settings, particularly concerning PM concentrations and CO₂ levels in secondary school classrooms. Significant correlations were observed between these variables and a variety of emotions, highlighting positive associations between CO₂ and negative emotions such as anger and disgust. PM showed weak correlations with emotions, for example, a significant negative correlation with surprise. Additionally, PM_{2.5} presented a positive correlation with happiness, and PM₁₀ with anger. CO₂ showed a posi-

tive correlation with anger and a negative correlation with neutral emotion. Although some relationships and patterns have been established, the relatively low levels of environmental factors may limit the variability in emotions detected, potentially reducing the strength of observed correlations.

The results of this study are noteworthy for the models for neutral emotion, fear, sadness, surprise, and happiness to explain a significant portion of the variance in these emotions, ranging from 62% to 36%, respectively.

In the case of neutral emotion, an increase in PM_{10} levels initially increases the expression of this emotion, but the quadratic term for PM_{10} reduces this effect. Similarly, for sadness, an increase in PM_1 levels is associated with a slight increase in the expression of this emotion, but the effect diminishes when considering its quadratic term. This suggests that the effect is not linear, and higher levels of PM might eventually have a negative impact. In the case of fear, an increase in CO_2 levels is associated with an increase in the expression of this emotion. This indicates that higher CO_2 levels can intensify fear, suggesting a direct and positive relationship between these factors.

The findings of this study present theoretical, methodological, and practical contributions. Regarding the theoretical contribution, this study significantly adds to the limited existing literature that links environmental conditions with emotions.

The methodological contribution is the use of affordable technology for monitoring environmental variables, combined with emotional recognition systems. This approach provides an alternative to traditional self-reports in studying mood and comfort regarding environmental conditions.

Regarding the practical contributions, first, classroom design is becoming increasingly important, with recommendations focused on creating stimulating, safe, and sustainable spaces, where technology plays an essential role in optimizing learning [40].

Second, real-time monitoring of indoor conditions, like PM and CO_2 levels, offers a proactive way to manage air quality in schools. By continuously tracking these factors, schools can plan and quickly respond to worsening conditions, reducing potential negative impacts on students' well-being. This is especially important in spaces with higher CO_2 levels, like crowded classrooms or during physical education.

Finally, advanced and affordable technology, characteristic of the Fourth Industrial Revolution, brings schools closer to smart classrooms. In these spaces, the pedagogical, technological, and environmental dimensions are interconnected, creating a more adaptive and effective setting for learning [41].

There are several limitations to this study. Firstly, its non-experimental design means that direct manipulation of environmental variables or controlled exposure of participants to different conditions was not possible, preventing the establishment of causal relationships between these variables and the observed emotions. Although significant correlations were identified, the influence of confounding variables or other uncontrolled factors cannot be entirely ruled out. Another limitation is the lack of gender diversity among the participants, as all the teachers involved were female, which might impact the generalizability of the findings regarding emotional responses. Finally, it is important to acknowledge the potential limitations in the accuracy of the sensors and the risk of measurement errors.

Looking forward, future research could explore the impact of other region-specific factors relevant to air quality on students' emotions. Additionally, studies combining multiple environmental factors and their cumulative effects on emotional responses could provide a more comprehensive view of the environmental influences. Investigating the interaction of these pollutants with other variables, such as temperature, humidity, and noise, would also contribute to a deeper understanding of the dynamics of environmental factors in educational settings.

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Institutional Review Board Statement: The researchers collected data during regular class hours, so ethics approval was requested by the Ethics Committee of the University Rovira i Virgili. They reviewed and approved this experiment with the reference number: CEIPSA-2021-TD-0019 (28 January 2022). Moreover, at the beginning of each academic year, parents of all students at the school sign a consent form for or against their children being photographed or recorded. Students without parental consent sit out of camera range. For the collection of environmental data in the classroom, this study underwent an additional ethical review and was approved with the reference: CEIPSA-2021-PR-0018.

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: The data are unavailable due to privacy and ethical restrictions.

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