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# Application of ChatGPT Plus in Predictive Analysis of Particulate Matter Levels in Industrial Environment of Glucose Syrup and Maltodextrin

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**Abstract:** This study examines the variation of Particulate Matter levels in eight work areas and evaluates the correlation between Particulate Matter levels and measurement time. The observed areas include starch warehouse, starch damping, coal storage, finished goods, load out, maintenance workshop, chemical warehouse, and bagging house. Data collection was conducted periodically over six quarters from 2021 to 2022. The analysis results showed significant variations in Particulate Matter levels between work areas. A strong positive correlation was found in the 'load out' area (r=0.791), but it was not statistically significant (p=0.061). In contrast, the 'starch warehouse' area showed a strong negative correlation (r=-0.662), but was also not significant (p=0.152). The use of ChatGPT Plus in this study facilitated data analysis and prediction of Particulate Matter levels. This Artificial Intelligence technology is able to process historical data, perform exploratory analyses, and develop prediction models such as AutoRegressive Integrated Moving Average and linear regression. Further research with long-term data is needed to understand the dynamics of air pollution in industrial environments. This research contributes to the understanding of the impact of air quality on workers' health and demonstrates the potential use of AI technology in environmental data analysis and air pollution prediction.

**Keywords:** Air quality; ChatGPT plus; Industrial pollution; Particulate matter

## Introduction

The physical health of living beings is greatly influenced by a healthy environment. Healthy air quality is an essential component of a healthy environment (Sukmawati, Fitriadi, et al., 2022; Waworundeng et al., 2018). 80 per cent of Indonesia's 250 million people live in areas where average particulate pollution levels exceed the threshold as per WHO guidelines (Greenstone et al., 2019; Sukmawati, Adhicandra, et al., 2022). WHO has adopted important resolutions on air quality and health since 2015. The resolution recognizes air pollution as a risk factor for non-communicable diseases such as cancer, stroke, chronic obstructive pulmonary disease, asthma, and coronary heart disease, as well as the economic losses it causes (WHO, 2021). Markandeya's 2021 study showed that adults inhale and exhale about 8 liters of air every minute. However, when this air essential for life is contaminated, the adverse effects are felt not only on humans but also on plants, animals, and all living organisms (Markandeya et al., 2021). Good air quality plays an important role in influencing human health. In 2019 in South Africa, more than four million deaths related to exposure to particulate air pollution were recorded (Arowosegbe et al., 2021). In South Korea, it is

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estimated that lung and respiratory system disorders cause more than two million deaths due to air pollution, observed in both indoor and outdoor environments (Kim et al., 2015; Rantauni et al., 2022). Air pollution has become a major public health issue dueto its contribution to increased mortality and morbidity rates. Globally, an estimated seven million people die each year from indoor and outdoor air pollution (Sarkodie et al., 2019). The conclusion was that the indoor air PM2.5 level was twice the quality standard (Azhar et al., 2016). Research focusing on the short-term effects of air pollution on respiratory disease morbidity and mortality has been particularly highlighted, given the widespread nature of air pollution (Priyankara et al., 2021). Air pollutants can come from various human activities, including cooking in the kitchen, motor vehicle smoke, dust from industry, and cigarette smoke. Nitrogen dioxide (NO2) is the most toxic of all the oxides of nitrogen in the air (Arwini, 2020). PM2.5 is the main pollutant that reduces air quality; its concentration in the air should not exceed 10 microns (Umri, 2021). It found that industrial air pollution decreased in the Americas and European countries with high urban populations, in contrast to developing countries (Sarkodie et al., 2019).

Byproducts of unsustainable planning and management policies in the energy, agriculture, transport and industrial sectors often exacerbate air pollution (Sarkodie et al., 2019). In China, rapid urbanization and industrialization results in high levels of air pollution, affecting more residents and increasing the population's disease burden (Chung et al., 2022). Health problems such as respiratory problems and ARI (Acute Respiratory Tract Infection) can occur if the amount of dust particles exceeds the threshold (Sunaryo et al., 2021).

Industries that utilize raw materials such as flour, sugar, or starch can be a source of anthropogenic Particulate Matter, including Industry Glucose Syrup and Maltodextrin located in Cikande Banten Modern Industrial Estate. The process of processing and manipulating these materials can produce small particles capable of being dispersed in the air. During the boiler combustion process, flue gas emissions from the chimney produce pollutants. These discharged air emissions usually contain pollutants such as particulates (dust) or gases such as NO2 and SO2 (Jyoti et al., 2019). Dust particles are a source of non-radiation hazards (Udi et al., 2017). The type of industry, industrial processes and equipment, and their utilities greatly influence the air pollution emissions generated (Jyoti et al., 2019). The maximum levels and emission loads allowed to enter or be introduced into the ambient air are known as emission quality standards for stationary sources (Patihawa et al., 2019). Dust particulates with a size of less than ten μm are called Particulate Matter 10/PM10, which has the ability to enter the human respiratory tract. Particulates greater than 2.5 μm are categorized as inhalable particulates, while respiratory particulates below 2.5 μm are called Particulate Matter 2.5/PM2.5. These small particles can reach the inner respiratory tract of humans (Udi et al., 2017). The impact rate of Particulate Matter On human health depends largely on the type of particle and the degree of pollution. Particulate Matter can cause various health complaints in the respiratory system, including asthma, bronchitis, and decreased lung function, as well as impact cardiovascular disease and potentially even cause premature death. This is evident in research conducted on the furniture industry in Surabaya (Sunaryo et al., 2021). One important component that can affect the health level of the workforce is indoor air quality (Budi et al., 2011). In general, air quality is measured by measuring the concentration of air pollution parameters that are higher or lower than the National Ambient Air Quality Standard values (Kurniawan, 2018).

ChatGPT has listed itself as "the fastest-growing consumer app in history", with over 100 million users since its launch in November 2022. The uniqueness of ChatGPT lies in its basic technology, namely the model Generative Pre-trained Transformer (GPT). The model can be trained using various machine and text-learning techniques, allowing ChatGPT to generate answers that resemble human writing. So far, several companies have adopted the use of these AI Chatbots to replace employee functions. ChatGPT is thought to have significant potential in revolutionizing the world of AI, including the possibility of unifying human reasoning with machines. ChatGPT also has the potential to change how various jobs are done. As a chatbot developed using OpenAI technology, ChatGPT is able to communicate like humans. Users can start using it by creating an OpenAI account for free (Haleem et al. 2022). ChatGPT Plus can be used to understand a given data's type and structure, including variables such as levels of Particulate Matter, observation period, and work area. This tool helps in the initial data processing process and performs data transformations such as encoding categorical variables.

The research in this study is of significant importance because it provides an in-depth understanding of the effect of air quality, particularly Particulate Matter levels, on human health and the environment. Against the backdrop of increasing health cases due to air pollution in various parts of the world, this research becomes relevant in the context of public health and environmental sustainability. Notably, this study explores the impact of industries utilizing raw materials such as flour, sugar, or starch on increasing Particulate Matter in the air. The application of ChatGPT Plus in the predictive analysis of Particulate Matter levels in the work area of the Glucose Syrup and Maltodextrin Industry is a new innovation in this study. The use of advanced AI technologies such as ChatGPT Plus in data analysis and predictive model generation opens up opportunities to understand air pollution patterns and trends in a more efficient and accurate way. This provides new insights that can be used to formulate appropriate policies and interventions to reduce the health risks and environmental impacts of air pollution. Therefore, the main objective of this research is to evaluate and predict Particulate Matter levels in industrial work environments using the latest data analysis methods, as well as provide practical recommendations based on scientific evidence for improving air quality and occupational health. This research not only contributes to the field of environmental health science, but also strengthens the role of AI technology in environmental data research and analysis.

## Method

The focus of this research is on evaluating the level of Particulate Matter in the Glucose Syrup and Maltodextrin Industrial environment in eight work areas of starch warehouse, starch damping, coal storage, finished goods, load out, maintenance workshop, chemical warehouse, and bagging house located in Modern Industrial Estate, Cikande Banten. Observational data are used to identify and analyze variations and patterns in Particulate Matter levels in industrial contexts, as well as develop predictive models to understand future Particulate Matter level dynamics.

In this study, data collection was carried out through measuring Particulate Matter levels referring to the NIOSH 0600 Method Specification 1994 edition. This measurement is carried out periodically in eight industrial work areas for six quarters, covering the period 2021 to 2022. The collected data includes Particulate Matter concentration values and relevant measurement times. This research adopts a quantitative approach, where data is collected and analyzed in numerical format. This process specifically aims to measure the level of Particulate Matter in the work environment of the Glucose Syrup and Maltodextrin industries. This quantitative approach allows researchers to observe a number of locations simultaneously, with the aim of identifying relationships or differences that arise in certain variables. Therefore, this study involved observing Particulate Matter levels at eight different locations in the industry's work environment at the same time.

Statistical analysis is performed using Data Analysis on Open Source ChatGPT Plus, which serves to create an effective and informative data representation. Statistical analysis of the collected data includes descriptive analysis, which aims to provide an overview of the distribution of data. To identify patterns of changes in Particulate Matter levels over time, data is plotted in the form of trend charts. Next, statistical comparisons were made between various work sites to understand the differences in Particulate Matter levels in each area. This analysis also involves a correlation between Particulate Matter levels with other variables such as measurement time and work area location. It aims to predict future levels of particulate matter. Initially ChatGPT Plus processes datasets containing historical information about PM levels, including variables such as PM concentration, observation time, and location. This data is reconstructed and cleaned to ensure high data integrity and quality. Further exploratory analysis to understand patterns and trends in the data, including identification of relationships between variables and observation of Particulate Matter distribution. ChatGPT Plus then develops predictive models, such as the ARIMA (AutoRegressive Integrated Moving Average) model or the linear regression model. These models are selected based on the characteristics of the data and the purpose of the analysis. The developed model is trained using historical data to study patterns and trends. Tests are conducted to evaluate the accuracy of the model using metrics such as Mean Squared Error (MSE) and coefficient of determination (R-squared). Once the model is validated, ChatGPT Plus uses the model to simulate and predict future PM levels.

## Result and Discussion

Statistical analysis provides information on the condition of Particulate Matter levels in eight industrial work areas. Descriptive statistics involve calculating basic statistics such as mean, median, mode, range, and standard deviation. This will provide an overview of Particulate Matter levels as a whole and per work area.

### *Descriptive Statistics*

Figures 1a to 1h provide detailed information on PM levels in each industrial work area. Each table presents descriptive statistics that help in understanding the variation and distribution of PM levels in the environment. The analysis results show that there is a significant variation in the Particulate Matter levels in the various industrial work areas observed. This variation is indicated by the high standard deviation (0.347) compared to the mean (0.224). PM levels varied from very low (0.02) to quite high (2.20), indicating significant differences in environmental conditions between times or between work areas. The Particulate Matter distribution is not completely symmetrical and tends to be slightly skewed towards lower values, with some significantly higher values that may signify specific instances where Particulate Matter levels are significantly elevated.

Analysis results on PM10 and PM2.5 came from outside air, although the source of particles differs depending on the environment (Morawska et al., 2017). Indoor PM2.5 concentrations are generally lower compared to outdoor (Rovelli et al., 2014). Different indoor PM2.5 and sub-micron particle concentration levels in hospitals show significant information about indoor air quality in healthcare facilities (Taushiba et al., 2023).

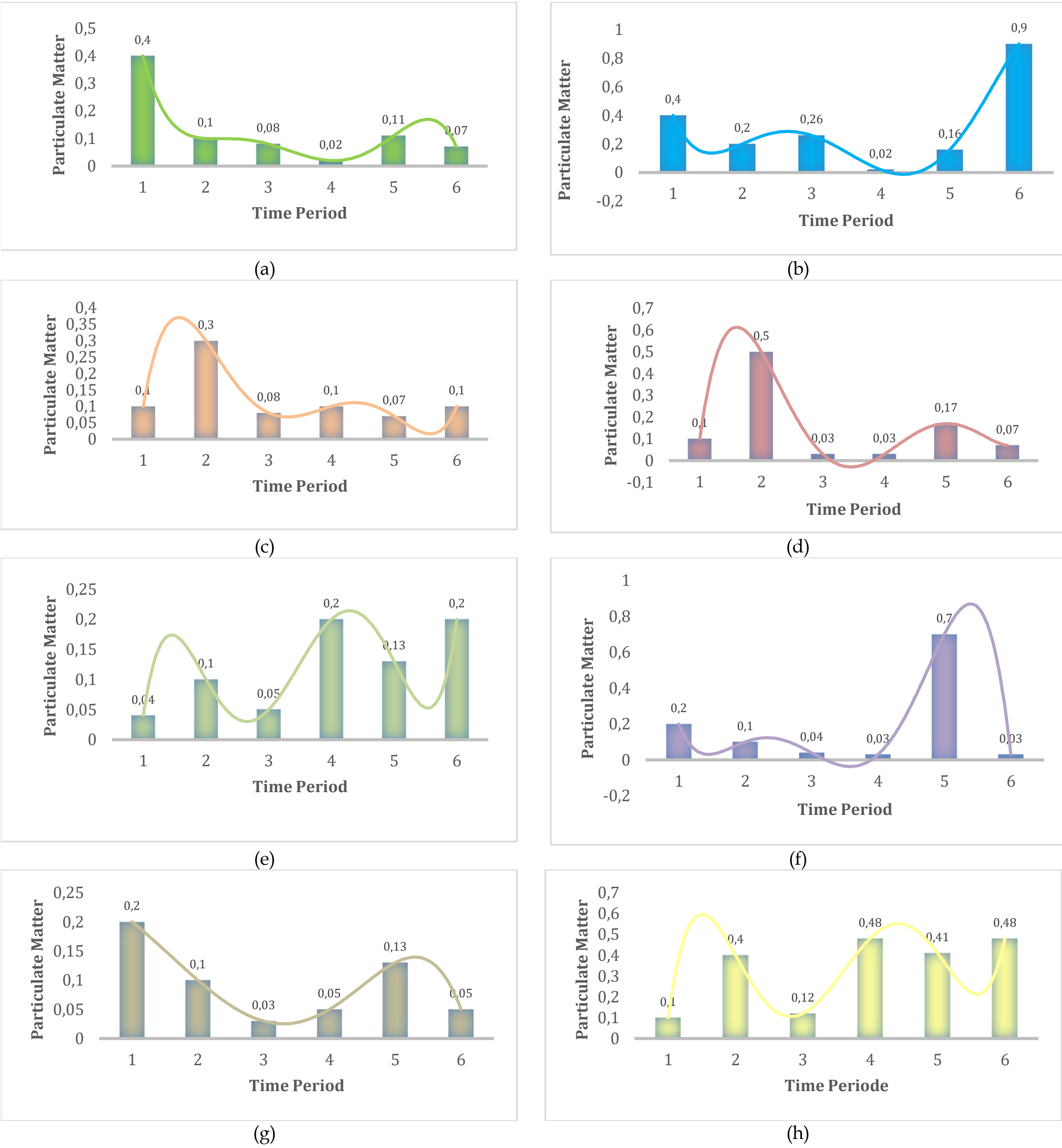



**Figure 1.** Mean particulate matter value in a) Starch warehouse, b) Starch damping, c) Coal storage, d) Finished goods, e) Load out, f) Maintenance workshop, g) Chemical warehouse, h) Bagging house. Time period: 1) 3rd quarter (September) 2021; 2) 4th quarter (December) 2021; 3) 1st quarter (March) 2022; 4) 2nd quarter (June) 2022; 5) 3rd quarter (September) 2022; 6) 4th quarter (December) 2022

**Table 1.** Statistical Distribution of Particulate Matter Levels

| Statistics | Value |
|---|---|
| Number of Observations | 48 |
| Average | 0.224 |
| Standard Deviation | 0.347 |
| Minimum | 0.020 |
| Quartile 25% | 0.065 |
| Median (Quartile 50%) | 0.100 |
| Quartile 75% | 0.215 |
| Maximum | 2.200 |

*Trend Analysis*

The figure 2 shows that Particulate Matter levels vary over time. There are periods where Particulate Matter levels increase sharply, followed by a decline. There are several points where the level Particulate Matter rose significantly. This can indicate certain events that affect environmental conditions, such as changes in production processes, maintenance activities, or other external factors. The chart does not show a clear trend up or down consistently over the observed period. This indicates that the level Particulate Matter influenced by various factors that may change over time. During 2014–2018, the proportion of PM2.5 in most of southern China's most populous cities averaged a slight but consistent increase (from 58.5% to 59.2%) (Zhang et al., 2022). China has increased its use of non-fossil energy to 15% since 2017. This was able to reduce annual average PM2.5 levels in North and South China by 28%, dropping from 50.8 μg/m³ to 36.7 μg/m³ (Li et al., 2022).

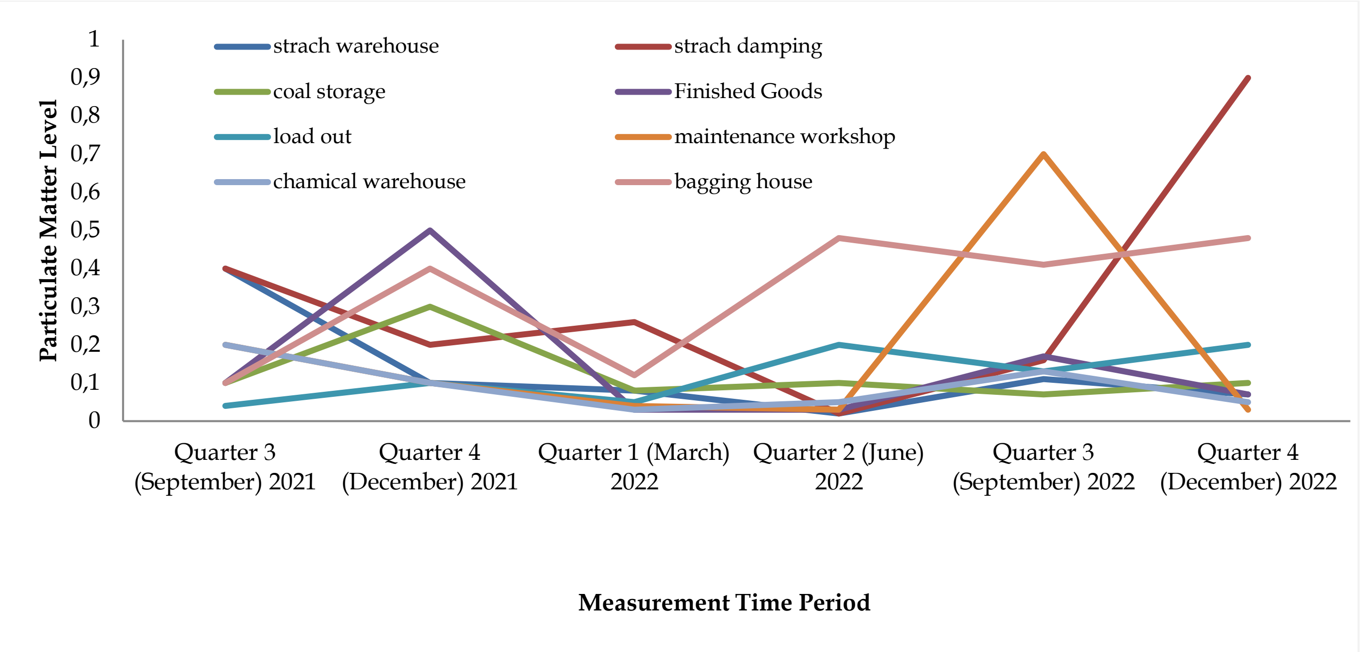



**Figure 2.** Particulate matter level trends

*Comparison of Particulate Matter Levels between Work Areas*

There is a significant variation in Particulate Matter levels between work areas shown in Figure 3. Areas such as "starch damping" have an average of levels Particulate Matter which is higher compared to other areas. Some work areas show levels Particulate Matter relatively higher ones, such as "starch damping" and "bagging house". At Work Area "Fear Damping", is an area of starch processing that involves manipulation of dry raw materials and powders. It inherently tends to release particulates into the air. This process of drying and grinding raw materials increases the chances of fine particulate emissions into the atmosphere of the working environment. While in the work area "bagging house" relates to the packaging activities of the final product. This process involves the transfer of materials from one container to another or filling into packaging, which can result in agitation and release Particulate Matter into the air. The application of sealing films, sealing caps, and pads in educational buildings showed a reduction in air leakage by 37% and a reduction in fine dust by up to 22%, as verified through blower door experiments (Yang et al., 2022). Opening windows at night and shading with roller blinds provide ventilation benefits and PM2.5 reduction indoors (Zhong et al., 2020). Station design, tunnel depth, thermal conditions, passenger density, and outdoor environmental conditions greatly affect the Level Particulate Matter indoors (Passi et al., 2021).

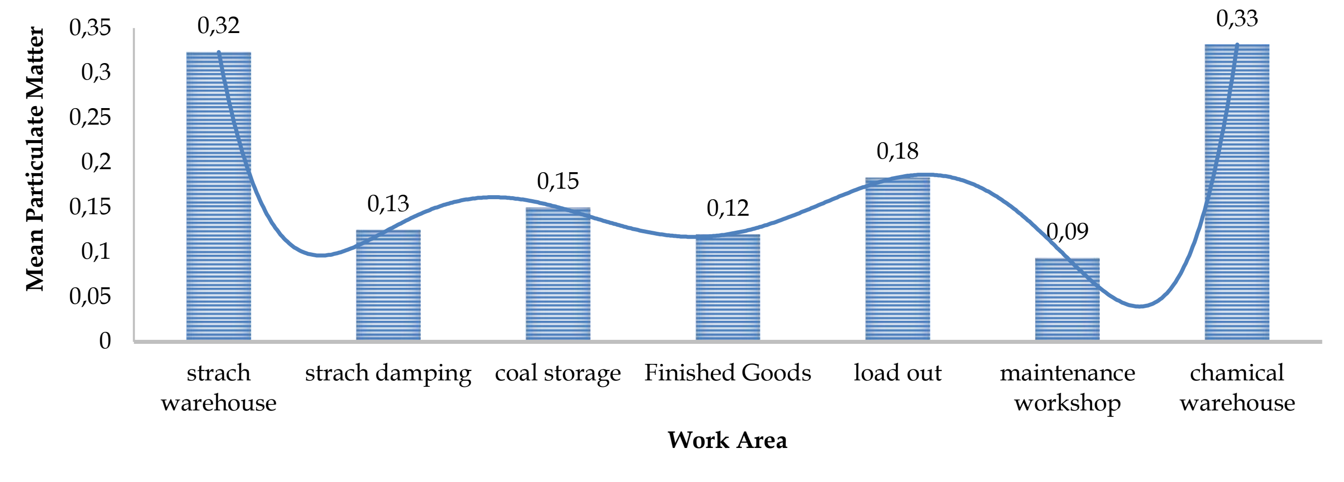



**Figure 3.** Comparison of particulate matter between work areas

**Table 2.** Particulate Matter Level Analysis Value

| Work Area | count | mean | std | min | 25% | 50% | 75% | max | median | modus | range |
|---|---|---|---|---|---|---|---|---|---|---|---|
| starch warehouse | 6 | 0.130 | 0.136 | 0.020 | 0.073 | 0.090 | 0.108 | 0.400 | 0.090 | 0.020 | 0.380 |
| starch damping | 6 | 0.323 | 0.309 | 0.020 | 0.170 | 0.230 | 0.365 | 0.900 | 0.230 | 0.020 | 0.880 |
| coal storage | 6 | 0.125 | 0.087 | 0.070 | 0.085 | 0.100 | 0.100 | 0.300 | 0.100 | 0.100 | 0.230 |
| Finished Goods | 6 | 0.150 | 0.179 | 0.030 | 0.040 | 0.085 | 0.153 | 0.500 | 0.085 | 0.030 | 0.470 |
| load out | 6 | 0.120 | 0.070 | 0.040 | 0.063 | 0.115 | 0.183 | 0.200 | 0.115 | 0.200 | 0.160 |
| maintenance workshop | 6 | 0.183 | 0.261 | 0.030 | 0.033 | 0.070 | 0.175 | 0.700 | 0.070 | 0.030 | 0.670 |
| chemical warehouse | 6 | 0.093 | 0.064 | 0.030 | 0.050 | 0.075 | 0.123 | 0.200 | 0.075 | 0.050 | 0.170 |
| bagging house | 6 | 0.332 | 0.175 | 0.100 | 0.190 | 0.405 | 0.463 | 0.480 | 0.405 | 0.480 | 0.380 |

*Correlation*

Correlation analysis showed that most of the work areas exhibited insignificant correlations between measurement times and Particulate Matter levels. Seen in 'Figure 4 'and 'Table 3' although some areas such as load out and bagging house show a strong positive correlation, these results are not statistically significant enough to confirm the relationship. Therefore, further research with more extensive data and additional variables may be required to understand the dynamics of Particulate Matter levels in this industrial work environment.

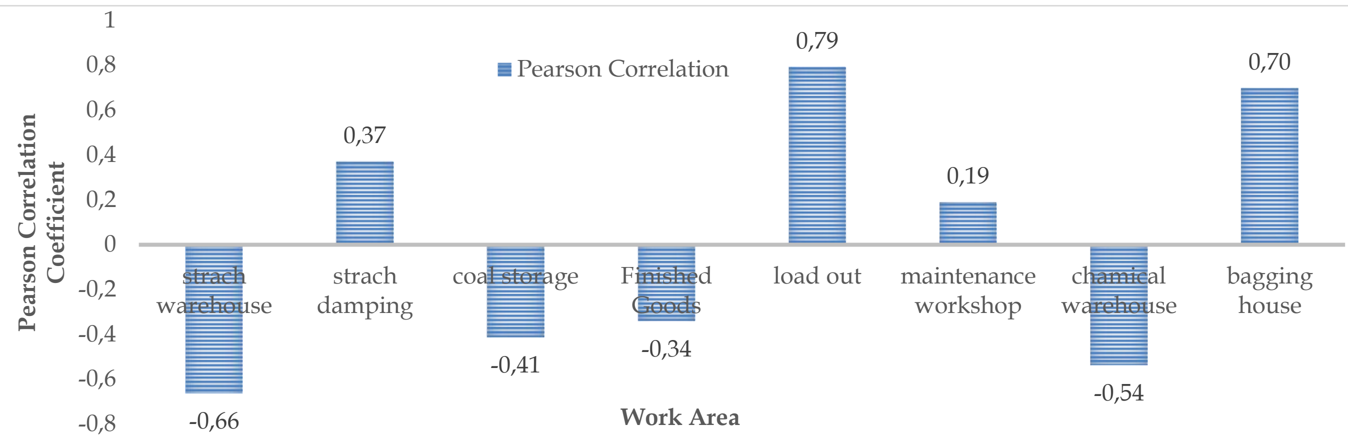



**Figure 4.** Correlation between time (observation period) and particulate matter levels

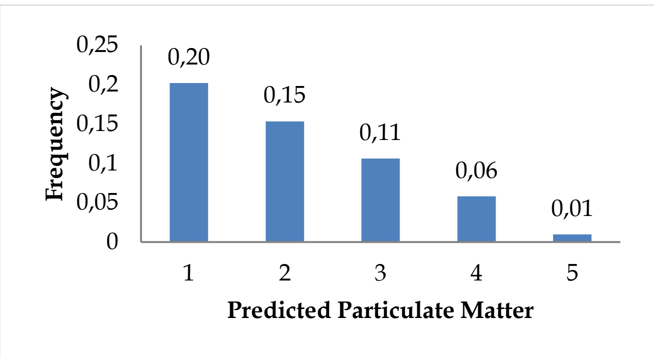
There are outlier data that may reflect changes in industrial operations or special activities that do not occur routinely, such as machine maintenance, production process changes, or other unusual activities that cause particulate emissions to increase temporarily. Further analysis with objective statistical criteria is needed to determine whether outlier data should be omitted. This includes examination of data distribution and the use of statistical methods to identify outliers. There is a strong correlation between indoor and outdoor PM10 and PM2.5 concentrations, with factors such as window type, heating season, and heating method being the main predictors of indoor pollution. The increase in PM outdoors has a significant impact on the increase indoors (Scibor, 2019). However concentrations of PM1.0, PM2.5, and PM10 in indoor and outdoor environments are similar, but not correlated (Mohammadyan et al., 2017). Although opening windows increases infiltration, it is often ineffective for removal Particulate Matter indoors

**Table 3.** Correlation Values between Time and Particulate Matter Rate

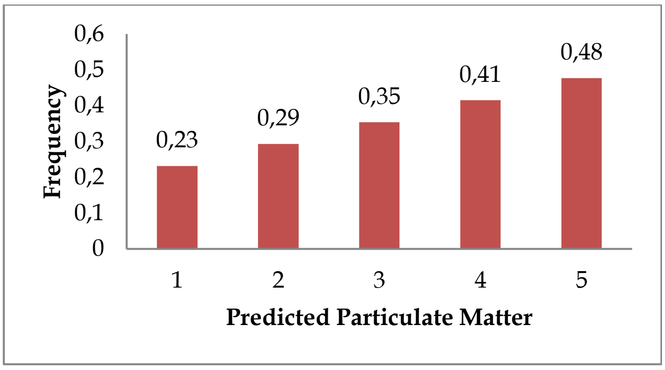
| Work Area | Pearson Correlation | P-value |
|---|---|---|
| starch warehouse | -0.661987712 | 0.152069119 |
| starch damping | 0.371214201 | 0.468755354 |
| coal storage | -0.412699026 | 0.41609701 |
| Finished Goods | -0.340023699 | 0.509620561 |
| load out | 0.791797293 | 0.060509927 |
| maintenance workshop | 0.190245255 | 0.718074915 |
| chemical warehouse | -0.536220359 | 0.27275979 |
| bagging house | 0.698251833 | 0.122840554 |

*Model Prediction*

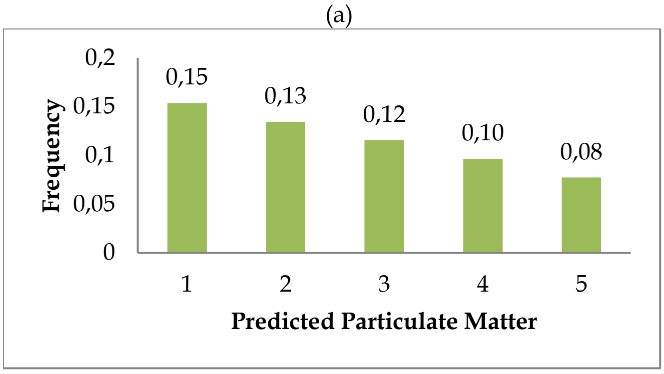
Data transformation or differentiation is required to achieve stationarity before the implementation of ARIMA models or other time series models. Given the non-stationary data conditions, consideration of alternative models, such as differentiated ARIMA or time-series models that account for stationarity, is important. In order to understand the patterns and make accurate predictions, this research has carried out further analyses through data transformation as well as testing various time series models on the eight work areas shown in Figure 5a to 5h. However, it is necessary to develop more sophisticated predictive models in analyzing levels Particulate Matter in an industrial environment. To achieve this, the study emphasizes the importance of additional data collection. This data includes operational factors such as production processes, working hours, and maintenance activities that have the potential to affect emissions. In addition, environmental conditions such as temperature, humidity, wind speed, and other weather factors are also considered to affect the spread Particulate Matter. Finally, pollution control measures that have been implemented, including the use of filters or ventilation systems, also need to be considered in the analysis. Extreme Gradient Boosting (XGBoost)-based predictive models can be used to predict PM2.5 levels in Jakarta (Kanezar MS et al., 2023). The prediction model for the average hourly PM2.5 concentration in the room uses Random Forest Regression (RFR) and Linear Regression (MLR) models that are based on easily accessible indicators. Results show that RFR models with machine learning methods have better prediction performance compared to classic MLR models. This suggests that RFR algorithms may be useful for predicting indoor air pollutant concentrations (Shi et al., 2023).



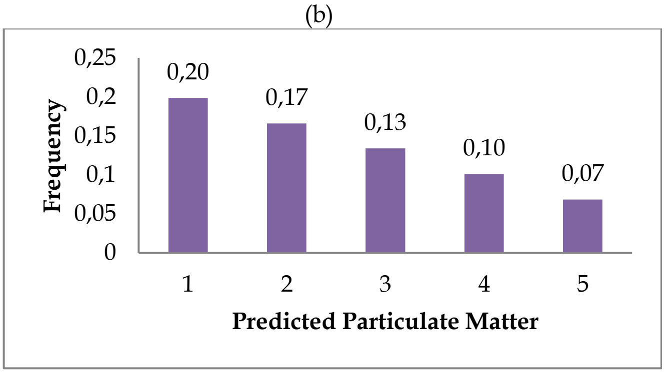

(a)




(b)




(c)




(d)

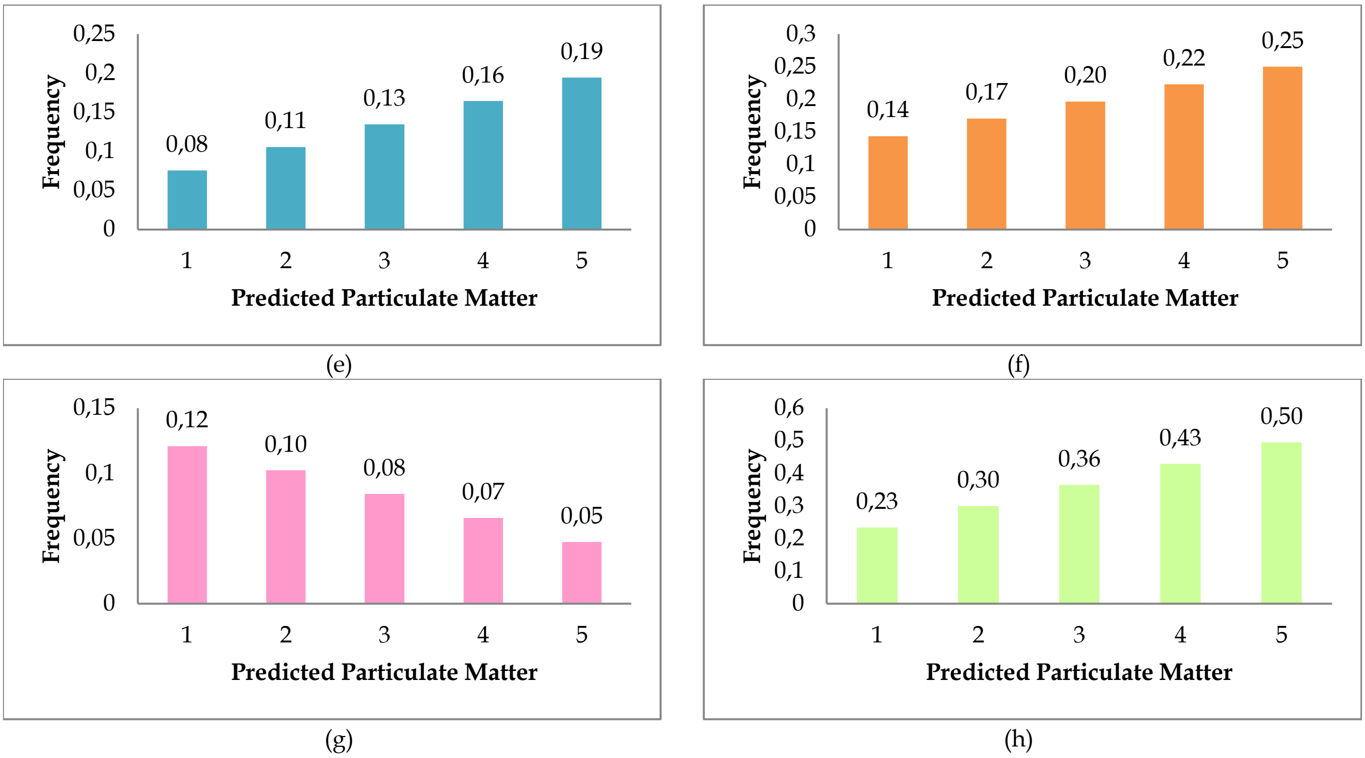



**Figure 5.** Predicted particulate matter value in a) Starch warehouse, b) Starch damping, c) Coal storage, d) Finished goods, e) Load out, f) Maintenance workshop, g) Chemical warehouse, h) Bagging house

The results of the study include important aspects related to the level of Particulate Matter in the industrial environment of Glucose Syrup and Maltodextrin. The analysis showed significant variation in Particulate Matter levels between work areas and over time. Potential causes of these variations can be differences in operational processes, the use of raw materials, or environmental conditions. High levels of particulate matter can be a potential indicator for occupational health issues and environmental impact—the implications of these findings for worker health and the need for mitigation strategies. There are limitations in the data and research methodology, such as the accuracy of Particulate Matter measurements or limitations in predictive models used in designing more comprehensive follow-up studies. Based on analysis for pollution control in the work area including improving ventilation systems, using emission control equipment, or changes in production processes. Identify areas that require further research, including long-term data collection, analysis of additional factors that might affect Particulate Matter levels, and development of more robust predictive models.

## Conclusion

This study revealed significant variations in Particulate Matter (PM) levels in eight work areas of the Glucose Syrup and Maltodextrin industries in Cikande Modern Industrial Estate, Banten. Some areas such as 'load out' and 'bagging house' showed a strong positive correlation with measurement time, however this correlation was not statistically significant. High PM levels in some areas indicate potential health risks for workers, especially in terms of respiratory disorders and cardiovascular disease. The use of ChatGPT Plus in this study helps in the process of analysing and predicting PM levels. By utilising AI technology, ChatGPT Plus is able to process historical data, perform exploratory analyses, and develop prediction models such as ARIMA and linear regression. The prediction results show variations in PM levels influenced by operational factors and environmental conditions.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The acknowledgments come at the end of an article after the conclusions and before the notes and references.


**Author Contributions**
We strongly encourage authors to include author contributions and recommend using credit for standardised contribution descriptions. Author's names are written in their initials and bold.


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**Conflicts of Interest**
Following our policy on conflicts of interest, please include a conflict of interest statement in your manuscript

here. Please note that this statement is required for all submitted manuscripts. If no conflicts exist, please state, "There are no conflicts to declare."

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