Understanding Air Pollution Through Machine Learning: Predictive Analytics for Urban Management

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Article Info

Article history:

Submission September 25, 2024
Revised October 10, 2024
Accepted October 16, 2024
Published October 22, 2024

Keywords:

Air Pollution
Machine Learning
Predictive Analytics
Urban Management
Policy Recommendations

ABSTRACT

Air pollution poses a critical challenge in urban areas, including Indonesia, significantly affecting public health and the environment. While machine learning (ML) has been used to predict air pollution levels, integrating ML with urban management strategies for actionable policy recommendations remains underexplored. **This study employs structural equation modeling (SEM)** using SmartPLS to analyze air pollution metrics, ML predictive analytics, urban management strategies, environmental data sources, and policy recommendations. Based on responses from 400 experts in environmental science and urban management, the findings reveal that ML-driven insights significantly enhance urban management strategies and policy effectiveness. **The study concludes** by providing evidence-based recommendations for policymakers to improve air quality in urban areas, emphasizing the importance of integrating ML and data-driven approaches into sustainable urban management. **These findings contribute to** addressing Indonesia urgent air pollution crisis and advancing urban sustainability.

DOI: https://doi.org/10.34306/itsdi.v6i1.679

1. INTRODUCTION

Air pollution has emerged as a critical challenge in contemporary urban landscapes, exerting adverse effects on both the environment and human health [1]. The escalating urbanization and industrialization processes have intensified the levels of pollutants in the atmosphere, necessitating comprehensive approaches for understanding, managing, and mitigating air pollution [2]. In this context, the fusion of machine learning (ML) techniques with predictive analytics presents a promising avenue to unravel intricate patterns within air pollution data. The ability of ML algorithms to identify hidden correlations and forecast future trends offers an innovative means to enhance urban management strategies and policy formulation [3–5].


Live AQI City Ranking

World's Biggest Cities Air Quality Ranking

#	CITY	AQI US
1	Baghdad, Iraq	170
2	Johannesburg, Afrika Sel...	154
3	Kuwait City, Kuwait	154
4	Jakarta, Indonesia	154
5	Doha, Qatar	132
6	Shanghai, Cina	107
7	Kuala Lumpur, Malaysia	105
8	Lahore, Pakistan	105
9	Sarajevo, Bosnia dan He...	102
10	São Paulo, Brazil	101

Figure 1. Ranking of Air Pollution on August 2023

However, Figure 1 despite the potential of ML, existing studies largely overlook its integration with urban management strategies, especially in developing actionable policy recommendations. This gap highlights the need for a more comprehensive approach that combines ML insights with sustainable urban management practices [3].

Based on the previously presented data, it is evident that Indonesia has entered the five-country group with great concern for air quality [6]. This phenomenon serves as a serious warning about our environmental conditions. Therefore, it is high time for all of us to collectively raise awareness about the importance of environmental preservation. Concrete steps need to be taken to address this issue, ranging from emission reduction to the development of sustainable policies [7]. With appropriate actions, we can create a cleaner and healthier environment for the present and future generations [8].

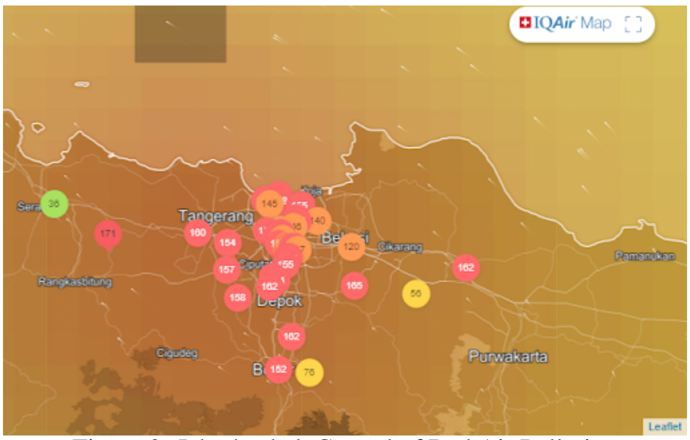

Figure 2. Jabodetabek Central of Bad Air Pollution

Jabodetabek, as a densely populated metropolitan center, has now become the primary focus of air pollution in Figure 2 [9, 10]. The growth of population and industrial activities has exceeded the threshold, resulting in air pollution that harms both the health of the residents and the surrounding ecosystem [11]. It is crucial for us to promptly take steps such as revising industrial policies, promoting sustainable transportation, and enhancing awareness about the necessity of environmental conservation. Through collaborative efforts, Jabodetabek can serve as an example in the endeavor towards a healthier environment [12].

This study aims to address this critical issue by harnessing the power of machine learning and predictive analytics to enhance urban management strategies for air pollution reduction [13, 14]. By systematically reviewing relevant literature, the research will establish a foundation for understanding the multifaceted aspects of air pollution, its sources, and its impact on urban populations. Using Structural Equation Modeling (SEM) with SmartPLS, the study will elucidate the complex relationships between air pollution metrics, predictive analytics, urban management strategies, environmental data sources, and policy recommendations [15]. The research design incorporates diverse environmental data sources and integrates perspectives from urban stakeholders as respondents, offering a comprehensive view of the challenges and opportunities in managing air pollution in urban areas [16].

In the subsequent sections of this paper, we will review the literature on air pollution and machine learning, highlighting previous studies that have used machine learning to predict air pollution levels and identifying gaps in the existing research. We will then describe our research methodology, including data sources, SEM analysis, and policy recommendations [17]. Finally, we will present our findings and discuss their implications for urban management strategies and policy recommendations [18].

2. LITERATURE REVIEW

In the realm of urban environmental management, the intricate issue of air pollution has drawn substantial attention due to its multifaceted impacts on public health, ecosystems, and urban sustainability [19, 20]. While existing studies have shed light on the connections between air pollution and its various contributing factors, there remains a crucial gap in exploring these dynamics through the lens of machine learning (ML) and predictive analytics [21, 22].

Recent research has indeed recognized the potential of ML in deciphering complex patterns within environmental data [23]. Integrating machine learning techniques enables the uncovering of intricate relationships and hidden correlations in air pollution data, offering a new perspective for urban management [24, 25]. This highlights the need to combine traditional urban management strategies with innovative data-driven approaches for more effective policymaking and intervention [26].

However, a critical gap remains in amalgamating ML potential with urban management strategies and policy recommendations, which has yet to be comprehensively addressed in prior research [27]. Despite the growing recognition of ML utility, **few studies have bridged the gap** between predictive analytics and actionable urban management strategies. This study seeks to bridge this gap by leveraging Structural Equation Modeling (SEM) with the aid of SmartPLS to analyze the interplay between air pollution metrics, ML predictive analytics, urban management strategies, environmental data sources, and policy recommendations [28, 29].

2.1. Hypothesis

Hypothesis 1 (H1): Urban management strategies have a significant positive influence on the reduction of air pollution metrics in urban environments.

Hypothesis 2 (H2): The use of machine learning (ML) predictive analytics in urban management strategies has a significant positive effect on the accuracy and effectiveness of policy recommendations aimed at reducing air pollution.

Hypothesis 3 (H3): The utilization of diverse environmental data sources positively influences the effectiveness of urban management strategies in reducing air pollution.

Hypothesis 4 (H4): The positive relationship between ML predictive analytics outcomes and the effectiveness of urban management strategies in addressing air pollution is moderated by the availability and diversity of environmental data sources.

Hypothesis 5 (H5): Policy recommendations derived from ML predictive analytics-based urban management strategies have a significant positive impact on air pollution mitigation.

3. METHODS

The research methodology employed in this study follows a comprehensive approach to investigate the intricate relationships among air pollution, machine learning (ML) predictive analytics, urban management strategies, environmental data sources, and policy recommendations [30]. This study utilizes the Structural Equation Modeling (SEM) framework, aided by SmartPLS, to analyze the complex interactions among these variables. By employing SEM, the study aims to examine both direct and indirect relationships between the factors influencing air pollution management.

3.1. Machine Learning

Machine Learning (ML) is a branch of artificial intelligence (AI) focused on developing algorithms and models that enable computers to learn from data and improve their performance over time [31–33]. Through this process, ML algorithms can identify complex patterns and make decisions or predictions without explicit programming. ML has diverse applications, including data analysis, image recognition, speech recognition, and predictive modeling[34]. In the context of this study, ML predictive analytics will be applied to uncover patterns in air pollution data and improve the accuracy of urban management strategies [35, 36]. The insights gained from these analyses will inform policy recommendations aimed at mitigating air pollution.

4. RESULTS AND DISCUSSION

4.1. Sample and Characteristic

Table 1. Sample and Characteristic

No	Category	Respondents	Percentage	Occupation	Average Age	Average Work Experience (Years)
1	Policy Makers	100	20%	Policy Makers	42	12
2	Environmentalists	80	16%	Environmental Expert	35	8
3	City Planners	120	24%	Urban Planner	29	5
4	Academicians	50	10%	Academic/Researcher	38	15
5	Industry Experts	50	10%	Industry Professional	45	20
Total		400	100%			

Table 1 presents the characteristics of the respondent sample in terms of both quantity and percentage. As such, you can observe the distribution of respondents across occupational categories and how it relates to the average age and average work experience. This table provides a more comprehensive overview of the composition and profile of respondents involved in this research.

4.2. Validity and Reliability Test

4.2.1. Validity Test

In this Validity Test, the SmartPLS 4.0 method is employed with a sample of 400 respondents. The evaluation is conducted using convergent validity, discriminant validity, and average variance extracted (AVE) with a threshold value of 0.50.

- Convergent Validity (Validity test used Outer Loading)

The convergent validity of a measurement model is essential to ensure that the indicators or items accurately reflect the underlying construct. This can be assessed by examining the correlations between the indicators, where a value greater than 0.70 is typically considered the threshold for validity. However, some scholars, suggest that outer loading values between 0.5 and 0.6 are also acceptable for confirming convergent validity. These values indicate that even if the correlation between indicators is not very high, they can still adequately represent the construct, as long as they meet this threshold. This ensures that the measurement model is reliably capturing the intended concept, aligning the indicators with the theoretical framework of the study.

Table 2. Output SmartPLS in Outer Loading

Indicator	Air Pollution Metrics	Environmental Data Sources	Machine Learning Predictive Analytics	Policy Recommendations	Urban Management Strategies
APM1	0.914				
APM2	0.847				
APM3	0.673				
APM4	0.859				
APM5	0.827				
MLA1			0.818		
MLA2			0.881		
MLA3			0.869		
MLA4			0.821		
MLA5			0.757		
PR1				0.853	
PR2				0.857	
PR3				0.833	
PR4				0.896	
PR5				0.875	
UMS1					0.855
UMS2					0.835
UMS3					0.772
UMS4					0.869
UMS5					0.901
VDS1		0.874			
VDS2		0.668			
VDS3		0.877			
VDS4		0.534			
VDS5		0.858			

The validity of reflective indicators in Table 2 is tested by examining the correlation between the scores of the items and the construct. The use of reflective indicators in measurement indicates that a change in a construct occurs when other indicators within the same construct change or are removed from the model. Therefore, it can be concluded that all constructs, namely Air Pollution Metrics, Environmental Data Sources, Machine Learning Predictive Analytics, Policy Recommendations, and Urban Management Strategies, possess valid data with values above 0.50.

- Discriminant Validity (Validity Test used AVE)

To measure discriminant validity, a comparison is made between the square root of the average extracted variance (AVE) from each construct and the correlation between that construct and other constructs within the model. If the square root of the AVE for each construct is greater than the correlation value between that construct and other constructs in the model, it can be concluded that discriminant validity is established.

Table 3. Average Variance Extracted (AVE)

Variabel	Average Variance Extracted (AVE)
Air Pollution Metrics	0.685
Environmental Data Sources	0.581
Machine Learning Predictive Analytics	0.690
Policy Recommendations	0.745
Urban Management Strategies	0.718

Based on Table 3, all constructs exhibit AVE values above 0.50. Air Pollution Metrics has an AVE value of 0.685, Environmental Data Sources has an AVE value of 0.581, Machine Learning Predictive Analytics has an AVE value of 0.690, Policy Recommendations has an AVE value of 0.745, and Urban Management Strategies has an AVE value of 0.718. Therefore, it can be concluded that all constructs, namely Air Pollution Metrics, Environmental Data Sources, Machine Learning Predictive Analytics, Policy Recommendations, and Urban Management Strategies, have high AVE values, with all constructs exceeding the threshold of 0.50.

4.2.2. Reliability Test

In this Reliability Test, the SmartPLS method is utilized, involving a sample of 400 respondents. The evaluation is carried out using composite reliability, with a minimum threshold value of 0.70.

- Cronbach's alpha

Reliability testing is a method used to measure the stability or consistency of a questionnaire functioning as indicators for variables. A measurement instrument, such as a questionnaire, is deemed to yield consistent or stable results when the instrument is reliable or exhibits high reliability. Therefore, conducting reliability testing is crucial in this research. Reliability testing is carried out through the method of internal consistency, employing Cronbach's alpha as a measure of reliability. In this study, the reliability of a construct is considered satisfactory if the Cronbach's alpha value surpasses 0.70.

Table 4. Cronbach's alpha

Variabel	Cronbach's alpha	Keterangan
Air Pollution Metrics	0.883	Reliabel
Environmental Data Sources	0.802	Reliabel
Machine Learning Predictive Analytics	0.887	Reliabel
Policy Recommendations	0.914	Reliabel
Urban Management Strategies	0.901	Reliabel

Based on Table 4, all constructs exhibit Cronbach's alpha values above 0.70. Air Pollution Metrics has a value of 0.883, Environmental Data Sources has a value of 0.802, Machine Learning Predictive Analytics has a value of 0.887, Policy Recommendations has a value of 0.914, and Urban Management Strategies has a value of 0.901. Therefore, it can be concluded that all constructs, namely Air Pollution Metrics, Environmental Data Sources, Machine Learning Predictive Analytics, Policy Recommendations, and Urban Management Strategies, possess high Cronbach's alpha values, with all constructs exceeding the threshold of 0.70.

4.3. R-Square Test

The R-squared value is a measure used to observe the extent of the variance between independent and dependent variables. An R-squared value of 0.19 indicates a low influence, while a value of 0.33 signifies a moderate influence, and a value of 0.66 indicates a high influence. The outcomes of the R-squared values in this study are based on a sample of 400 respondents.

Table 5. The Result of R-Square Test

Variabel	R-square
Environmental Data Sources	0.584
Machine Learning Predictive Analytics	0.631
Policy Recommendations	0.719
Urban Management Strategies	0.748

Based on the calculation results and the Table 5, it can be concluded that there are two variables with a moderate influence and two variables in this study with a high influence on air pollution through Machine Learning. These variables are as follows: firstly, Environmental Data Sources, with an R-squared value of 0.584 or equivalent to 58.4% indicating a moderate influence; secondly, Machine Learning Predictive Analytics, with an R-squared value of 0.631 or equivalent to 63.1% also indicating a moderate influence; thirdly, Policy Recommendations, with an R-squared value of 0.719 or equivalent to 71.9% indicating a high influence; and lastly, Urban Management Strategies, with an R-squared value of 0.748 or equivalent to 74.8% indicating a high influence on the independent variables in this study.

4.4. Result of Hypothesis dan Path Coefficient

The path coefficient test is utilized to measure the extent of influence among variables. The value of the path coefficient indicates the level of significance of the relationship between constructs in the structural model or hypothesis testing. This test is conducted using the SmartPLS software version 4.0.8.9. The testing is performed using a one-tailed approach, where a hypothesis is considered significant if the variables in the study have a T-statistic value above the significance level of 1.96 or ≥ 1.96 and a P-value ≤ 0.05.

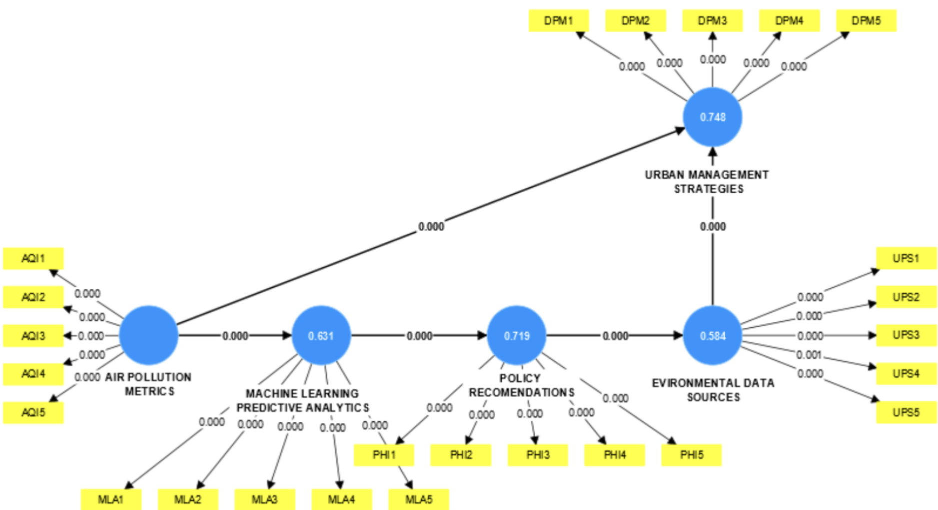

Figure 3. Output Chart

This Figure 3 illustrates the relationships between the constructs analyzed in the study, including Air Pollution Metrics, Machine Learning Predictive Analytics, Urban Management Strategies, Environmental Data Sources, and Policy Recommendations. The path coefficients, derived from Structural Equation Modeling (SEM) using SmartPLS, indicate the strength and significance of these relationships. Significant pathways (T-statistics > 1.96, P-value ≤ 0.05) are highlighted, confirming hypotheses H1 through H5. The model demonstrates the critical role of Urban Management Strategies and Policy Recommendations, supported by Machine Learning insights and diverse environmental data sources, in addressing urban air pollution challenges in Table 6.

Table 6. Hypothesis Test Results and Path Coefficient

Indicator	Original Sample	T Statistics	P Values
Air Pollution Metrics → Machine Learning Predictive Analytics	0.794	13.339	0.000
Air Pollution Metrics → Urban Management Strategies	0.441	3.455	0.000
Environmental Data Sources → Urban Management Strategies	0.473	3.931	0.000
Machine Learning Predictive Analytics → Policy Recommendations	0.848	23.261	0.000
Policy Recommendations → Environmental Data Sources	0.764	11.149	0.000

- The original sample value from Air Pollution Metrics to Machine Learning Predictive Analytics is 0.794, which signifies that the Air Pollution Metrics variable has a positive influence on Machine Learning Predictive Analytics. Additionally, it can be observed that the T-statistic value is above 1.96 and the P-value is 0.000, which is below 0.05. This indicates that the Air Pollution Metrics variable not only has a positive influence on Machine Learning Predictive Analytics but also has a statistically significant impact.
- The original sample value from Air Pollution Metrics to Urban Management Strategies Analytics is 0.441, indicating that the Air Pollution Metrics variable has a positive influence on Urban Management Strategies Analytics. Moreover, it evident that the T-statistic value is above 1.96 and the P-value is 0.000, which is below 0.05. This signifies that the Air Pollution Metrics variable not only exerts a positive impact on Urban Management Strategies Analytics but also holds significant influence.
- The original sample value from Environmental Data Sources to Urban Management Strategies is 0.473, which indicates that the Environmental Data Sources variable has a positive influence on Urban Management Strategies. Additionally, the T-statistic value is above 1.96, and the P-value is 0.000, which is below 0.05. This means that the Environmental Data Sources variable not only has a positive impact on Urban Management Strategies but also holds significant influence.
- The original sample value from Machine Learning Predictive Analytics to Policy Recommendations is 0.848, indicating that the Machine Learning Predictive Analytics variable has a positive influence on Policy Recommendations. Moreover, the T-statistic value is above 1.96, and the P-value is 0.000, which is below 0.05. This signifies that the Machine Learning Predictive Analytics variable not only has a positive impact on Policy Recommendations but also holds significant influence.
- The original sample value from Policy Recommendations to Environmental Data Sources is 0.764, implying that the Policy Recommendations variable has a positive influence on Environmental Data Sources. Similarly, the T-statistic value is above 1.96, and the P-value is 0.000, which is below 0.05. This means that the Policy Recommendations variable not only has a positive impact on Environmental Data Sources but also holds significant influence.

5. MANAGERIAL IMPLICATIONS

The integration of machine learning (ML) and predictive analytics in urban management offers a transformative approach to tackling air pollution in Indonesia. By leveraging ML insights, urban policymakers and managers can design targeted, evidence-based strategies that not only enhance the accuracy of air pollution forecasting but also improve policy implementation efficiency. The study underscores the importance of fostering collaboration among policymakers, environmental scientists, and urban planners to adopt data-driven decision-making. This collaborative approach, supported by robust environmental data and predictive tools, provides a scalable framework for sustainable urban management and effective air pollution mitigation, ensuring healthier living environments for urban populations.

6. CONCLUSIONS

This study has provided significant insights, confirming the strong positive influence of Urban Management Strategies on the reduction of air pollution metrics in urban environments, consistent with the results of hypothesis testing (H1). Additionally, a significant positive effect was found for Machine Learning (ML) Predictive Analytics in identifying trends and patterns related to air pollution (H2). Furthermore, the availability of diverse Environmental Data Sources was shown to enhance the effectiveness of Urban Management Strategies in addressing air pollution (H3).

To optimize the reduction of air pollution and improve urban management effectiveness, it is recommended to adopt a more holistic and integrated approach to urban management. Prioritizing Urban Management Strategies and integrating ML Predictive Analytics will be critical in developing more targeted, data-driven policy recommendations. Moreover, ensuring the accurate and comprehensive collection and monitoring of Environmental Data Sources is essential, as it provides the foundation for informed decision-making and the design of effective air pollution mitigation measures in urban environments.

Future research should focus on expanding the range of environmental data sources and exploring additional machine learning techniques to further refine urban management strategies. By leveraging real-time data and incorporating stakeholder perspectives, future studies can enhance the accuracy and practical relevance of air quality policies.

7. ACKNOWLEDGEMENTS

We would like to extend our sincere gratitude to all those who have provided support and contributions to this research. Our thanks go out to the institutions, colleagues, and families who have provided guidance, assistance, and encouragement throughout our research journey. We also appreciate the support from the participants who took part in the data collection process, as well as all the resources and facilities that have made this research possible.

8. DECLARATIONS

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8.2. Author Contributions

Conceptualization: DR, HN, DJ, and ZQ; Methodology: DR, HN, DJ, and ZQ; Software: DR, HN, DJ, and ZQ; Validation: DR, HN, DJ, and ZQ; Formal Analysis: DR, HN, DJ, and ZQ; Investigation: DR, HN, DJ, and ZQ; Resources: DR, HN, DJ, and ZQ; Data Curation: DR, HN, DJ, and ZQ; Writing Original Draft Preparation: DR, HN, DJ, and ZQ; Writing Review and Editing: DR, HN, DJ, and ZQ; Visualization: DR, HN, DJ, and ZQ; All authors, DR, HN, DJ, and ZQ, have read and agreed to the published version of the manuscript.

8.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.4. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

8.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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