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Impact of AI on Air Quality Monitoring Systems: A Structural Equation Modeling Approach Using UTAUT

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ABSTRACT

Artificial Intelligence (AI) technology in air quality systems is a potential solution to the complex challenges of global air pollution. This study applies the Unified Theory of Acceptance and Use of Technology (UTAUT) model with the participation of 100 respondents to investigate the factors affecting the adoption of this technology. Related variables include performance expectations, effort expectations, social influence, favorable conditions, usage behavior, trust in technology, perception of air quality issues and environmental impact is felt. This study explores the essential factors influencing the adoption and acceptance of this technology. The Structural Equation Modeling (SEM) method, with the support of smartPLS 4, was applied as the primary method to analyze the complex interaction between these variables. The main results of this study show that aspects such as performance expectations, effort expectations and facilitation significantly impact the intention to use this technology. On the other hand, social influence is also said to have a prominent impact. Through these findings, this paper provides relevant strategic guidance in developing promotional efforts and implementing this technology. In addition, the integrated theoretical framework proposed in this study offers valuable support for policymakers, technology developers, and practitioners in the environmental field. Collaborative efforts to improve air quality and contribute to sustainability are the main objectives of this research.

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1. INTRODUCTION

In the face of the complexity of global challenges related to air pollution, the utilization of Artificial Intelligence (AI) technology in Air Quality Systems holds promise as a potential solution. Integrating AI into air quality management offers new opportunities to effectively address air pollution-related issues. This paper, titled "Antecedents and Outcomes of AI Air Quality System Utilization: A Unified Theory of Technology Acceptance and Use Investigation", explores the factors that influence the adoption and utilization of AI-based Air Quality Systems [1].

Recent advances in AI technology have opened up new opportunities in various sectors. Among these, the application of AI in monitoring and managing air quality has gained significant attention due to its potential to provide accurate and timely assessments, aiding in effective pollution control and environmental protection [2]. However, the effective adoption and utilization of these advanced systems require a thorough understanding of the factors that drive their acceptance and usage among stakeholders.

To better understand the causes and effects of AI-based Air Quality Systems, this research presents an analysis based on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework [3]. Key variables in this study include performance expectancy, effort expectancy, social influence, facilitating conditions, and usage behavior. This study aims to identify the critical elements that affect how individuals, communities, and organizations adopt and accept AI-based air quality systems. To examine the intricate interactions between these variables, this study employs the Structural Equation Modeling (SEM) method, supported by SmartPLS software. This analytical approach allows for a more transparent understanding of the complex dynamics driving the adoption and use of AI-based Air Quality Systems [4, 5].

This investigation is expected to provide valuable insights for policymakers, technology developers, and environmental practitioners. By understanding the factors that influence the acceptance and utilization of AI-based Air Quality Systems, stakeholders can develop better strategies to promote and implement these technologies. Ultimately, this collaborative effort aims to improve air quality and sustainability, addressing the critical challenges posed by air pollution worldwide [6].

2. LITERATURE REVIEW

The utilization of AI technology to address the global challenge of air pollution has attracted widespread attention in scientific literature. Integrating AI into Air Quality Systems is considered a significant step forward in tackling severe air quality problems worldwide [7]. Environmental researchers and practitioners increasingly recognize the potential of AI to provide practical and innovative solutions for air quality monitoring and management [8].

In this study, "Antecedents and Outcomes of AI Air Quality System Utilization: A Unified Theory of Acceptance and Use of Technology Investigation", the Unified Theory of Acceptance and Use of Technology (UTAUT) serves as the essential theoretical framework. This model is crucial for understanding the factors that influence technological acceptance and adoption. UTAUT identifies key factors that impact technology usage behavior and intention, including performance expectancy, effort expectancy, social influence, facilitating conditions, and usage behavior [9].

In the context of AI Air Quality System utilization, Performance Expectancy reflects user expectations regarding improvements in air quality monitoring and assessment efficiency. Effort Expectancy refers to the perceived ease of use of AI technology in air quality management [10]. Social Influence represents the social factors affecting users' intentions, while Facilitating Conditions encompass supporting and environmental factors that enable technology adoption. Usage Behavior describes how the technology is applied in practice [11, 12].

Empirical research has demonstrated that the factors outlined by UTAUT significantly influence technology acceptance and adoption, including in the context of AI-based Air Quality Systems. However, the influence and role of each factor may vary depending on the context, environment, and user characteristics [13].

Additionally, the Structural Equation Modeling (SEM) analysis method, supported by SmartPLS software, has been widely applied in previous studies. This method facilitates the examination of interrelationships between complex variables while also validating the proposed theoretical model [14].

Overall, the scientific literature provides a strong foundation for exploring the utilization of AI technology in Air Quality Systems from both theoretical and empirical perspectives. This study aims to identify the key factors influencing the adoption of these technologies using the UTAUT framework and SEM analysis [15]. It is expected that this research will contribute to the development of practical solutions for enhancing global sustainability and air quality.

3. METHOD

This research aims to conduct an in-depth investigation of the antecedents and outcomes of the utilization of an Air Quality System enriched by Artificial Intelligence (AI), in line with the concepts of the Unified Theory of Acceptance and Use of Technology (UTAUT), to respond to the dynamics of global problems related to air pollution. The Structural Equation Modeling (SEM) analysis method, powered by SmartPLS 4 software, was the primary approach to test the conceptual model and unpack the intricate relationships carried by the variables described in the abstract and introduction (Figure 1) [16].

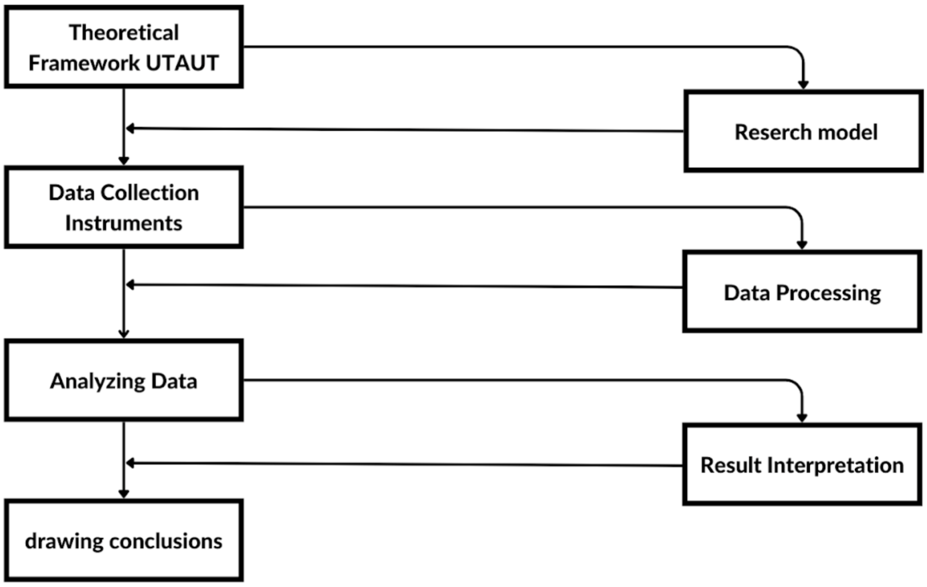

Figure 1. Research Methodology

UTAUT Theoretical Framework: The UTAUT theoretical framework was adopted as a conceptual tool in this study, helping to identify essential cluster variables that play a crucial role in describing and influencing the adoption and acceptance of AI technology in Air Quality Systems [17]. Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Use Behavior are among the variables investigated.

- Research Design: The research design involved a comprehensive cross-sectional survey approach. This study respondents include various stakeholders actively engaged in implementing the AI Air Quality System. Representative sampling will enable the generalization of the research results to multiple contexts, including students, academics, researchers, and practitioners in various related sectors [18].

- Data Collection Instrument: The survey instrument will be carefully constructed, considering the dimensions of the variables outlined in the UTAUT theoretical framework. Survey questions will be formulated to explore respondents perceptions and views on variables such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Use Behavior [19].

- Data Processing: The collected survey data will be analyzed through a Structural Equation Modeling (SEM) analysis approach, with smartPLS software providing the necessary analytical competencies. This method provides the capability of exploring intricacy relationships between complex variables while also allowing for testing and validating the proposed theoretical model [20].

- Data Analysis: Data analysis will involve comprehensive analytical steps. This includes model parameter estimation, model construction validation, and statistical hypothesis testing to detail the influence of each variable on the intention and behavior of using AI technology in Air Quality Systems [21].

- Interpretation of Results: The results of the analysis will be interpreted holistically and in-depth, providing a rich understanding of the dominant factors in the acceptance and utilization of AI technology in the

Air Quality System. The practical implications of these findings will be systematically explored, creating an effective guiding framework for policy makers, technology developers, as well as environmental practitioners [22].

Through this carefully designed methodology, it is hoped that this research will make an important contribution in unraveling the problems of adoption and acceptance of AI technology in Air Quality Systems, while encouraging real efforts in improving air quality and sustainable development on a global scale.

3.1. A Unified Theory of Acceptance and Use of Technology Investigation (UTAUT)

Based on a literature review, "UTAUT is a model to explain user behavior towards information technology. UTAUT is formulated with four core determinants of intention and usage: performance expectancy, effort expectancy, social influence, & facilitating conditions. Then each determinant influences behavioral intention and technology use" [23]. UTAUT consists of four main concepts, namely performance expectations, effort expectations, social influence and facilitation, which influence behavioral intention to use or use technology. In this framework, the structures and definitions of UTAUT are adapted to the context of the adoption and use of the AI Air Quality System. Performance expectations in this context are defined as the extent to which the use of technology will benefit users in addressing air quality issues. Expected effort measures the ease associated with using this technology. Social influence refers to users opinions about the beliefs of significant other people (such as family and friends) about the need to use this technology". The favorable condition is users perception regarding the availability of resources and support required to use the system. These terms may include technology infrastructure, technical support, and third-party support [24].

According to UTAUT, behavioral intention to use technology is thought to be influenced by performance expectations, effort expectations, and social influence. Behavioral purposes and enabling factors will affect the level of technology use. Additionally, it was determined that age, gender, and experience (without voluntariness, which was a component of the original UTAUT) were individual difference variables that may act as moderators in several interactions of the UTAUT construct. As shown in the overview provided in Figure 2 in this work [25], the notion evolved into a pillar of analysis in the development of a better knowledge of the adoption and use of AI Air Quality Systems.

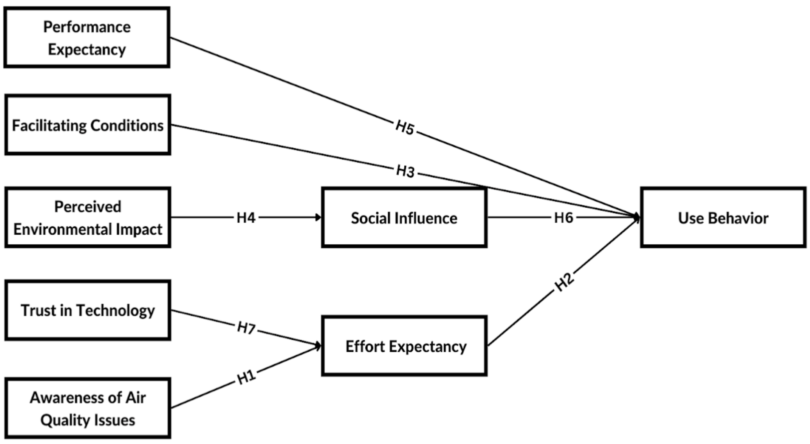

Figure 2. Research model

To analyze the literature relevant to UTAUT, we explored various sources of journals and conference proceedings relevant to this domain. This resulted in a dataset of many in-depth articles analyzed to uncover significant patterns and findings. From this analysis, most of the pieces refer to the original work of UTAUT as a common foundation in technology adoption studies. However, the implementation and expansion of the UTAUT concept in a broader context still needs to be improved. Our review and synthesis confirmed that some efforts have been made to expand the scope of UTAUT, although most of the published research still only focuses on a few aspects of the UTAUT constructs [26]. Enrichment, particularly with the introduction of new constructs, has been instrumental in expanding the theoretical dimensions of UTAUT. However, it is essential to note that adding such constructs is often done without a solid theoretical framework supporting the research context. These studies have yet to systematically select complementary mechanisms based on a proper theoretical foundation of the concepts elaborated in UTAUT. Introducing these complementary constructs can expand the scope and generalizability of the UTAUT theory [27].

3.2. Structural Model, Performance Indicators, and Hypotheses

This study examines the elements that affect how AI Air Quality Systems are used and accepted. To achieve this, the primary aspects of this study Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Use Behavior are emphasized [28]. This study also examines the significance of other variables, such as perceived environmental impact, awareness of air quality problems, and trust in technology. Figure 3 depicts the structural model of all aspects involved in this study adoption and implementation of AI Air Quality Systems.

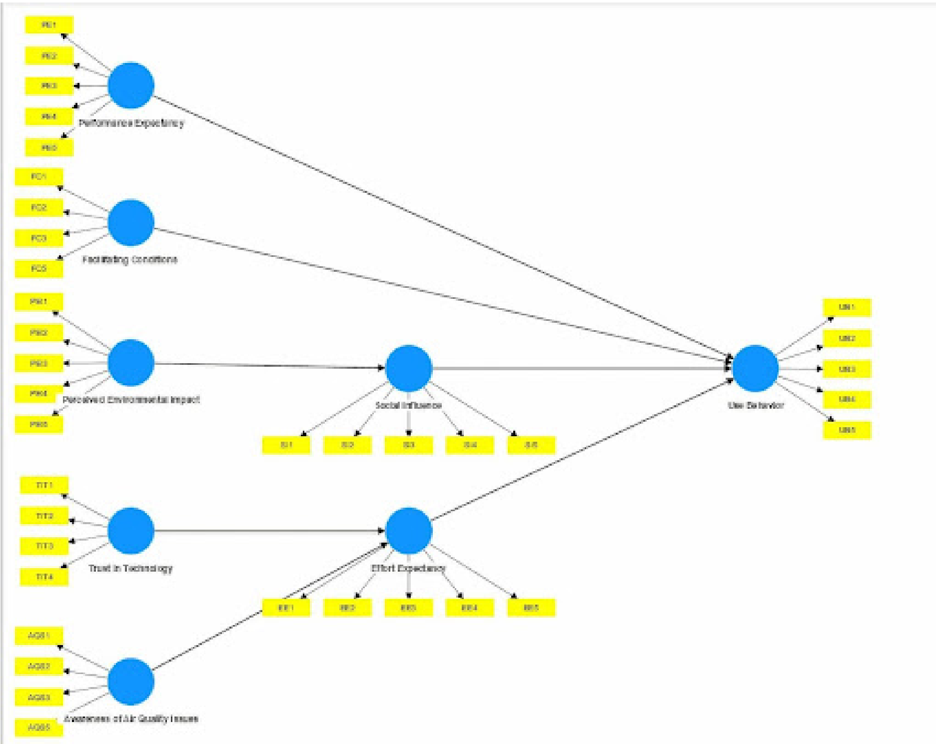

Figure 3. Structural model of the influence of acceptance and use of AI Air Quality System

With this framework, hypotheses have been formulated to test the relationship and influence between these variables in the context of acceptance and use of AI Air Quality Systems.

H1:Increased user awareness of air quality issues is positively associated with performance expectations in the context of AI Air Quality Systems, indicating that an understanding of environmental impacts can drive expectations of the technology performance.

H2: Lower effort expectations regarding using the AI Air Quality System could potentially inhibit usage behavior, indicating that perceived ease of use is an important factor in technology adoption.

H3: Facilitating condition factors, such as resource availability and support, have a positive impact on AI Air Quality System usage behavior, suggesting that a supportive environment can stimulate users to more actively utilize the technology.

H4: User perceptions of positive environmental impacts influence social influence, illustrating that individual views of positive impacts can influence influences from the surrounding social environment.

H5: Expectations of the performance of AI technology in addressing air quality issues influence usage behavior, reflecting the importance of belief in the benefits of using the technology.

H6: Social influence positively influences the usage behavior of the AI Air Quality System, indicating that the views and beliefs of the user's social environment can influence the use intentions and actions regarding the technology.

H7: The level of user trust in AI technology positively affects performance expectations, indicating that trust in the capabilities of technology is a factor that affects user expectations of the performance of the technology.

4. RESULT AND DISCUSSION

This research focuses on the context of utilizing the AI Air Quality System. The study involved a sample of 100 respondents who are potential users of the technology. The respondents selected had experience and knowledge related to air quality issues and the application of artificial intelligence technology. The sampling was carried out by taking into account inclusion criteria pertinent to the study goals, which are expected to give detailed insight into the relationship between variables like performance expectations, effort expectations, social influence, enabling conditions, and usage behavior toward the adoption and use of AI Air Quality Systems. Therefore, using this sample will give users a thorough understanding of the characteristics of this technology acceptability and use in the pertinent context.

4.1. Effect Size Value

Effect size analysis was carried out to assess the influence of predictor constructs on endogenous constructs. The many characteristics of performance expectations, effort expectations, social influence, facilitating conditions, and usage behavior are among the factors that impact how well AI Air Quality System is received and used. The analysis findings significantly affected performance expectations, effort expectations, social influence, and enabling circumstances. Furthermore, user trust and performance expectations are closely related [29, 30].

Table 1 and the visualization in Figure 3 illustrate the extent of influence of the factors of acceptance and use of the AI Air Quality System. These variables include performance expectancy, effort expectancy, social influence, facilitating conditions, usage behavior, user trust, user awareness of air quality issues, and user perception of environmental impacts. Considering these variables, it is expected to increase the acceptance and use of AI Air Quality Systems in relevant contexts [31].

The performance map study, which is depicted in Figure 1, indicated that there is a strong correlation between a number of elements that contribute to the acceptance and use of the AI Air Quality System. These variables include performance expectations, effort expectations, social pressure, and enabling circumstances. The effectiveness of facilities and services in the acceptance and use of AI Air Quality Systems are impacted by all of these interactions [32].

Table 1. Effect of acceptance and use of AI Air Quality System

Construct	AQI	EE	FC	PEI	PE	SI	TIT	UB
Awareness of Air Quality Issues		0.154						-0.022
Effort Expectancy					-0.142			
Facilitating Conditions			0.326					
Perceived Environmental Impact				0.820				0.413
Performance Expectancy					0.266			
Social Influence						0.504		
Trust in Technology		0.154						-0.099
Use Behavior								

4.2. Validity and Reliability Test

Data analysis using structural equation modeling (SEM) was carried out to foresee the effects of the variables and confirm the fit of the empirical model. Measurement model analysis (confirmatory factor analysis or CFA) and structural model analysis are the two stages of this analysis [33, 34]. While structural model analysis is used to assess the path influence between latent variables, CFA is used to test the validity and reliability of the research. The t-value of the normalized factor loadings and the anticipated path coefficients are indicators of the outcomes of structural model analysis.

Three criteria are used to gauge the convergent validity of CFA. First, standardized factor loadings are used to assess each index dependability. Second, reliability is assessed using Cronbach alpha and Composite dependability (CR). Third, Variance Extracted (AVE) is used to quantify the variation in the variable as a result of measurement error [35]. According to CFA convergent validity requirements, our study Cronbach and CR values for all latent variables were above 0.70, and the AVE for all constructs was higher than 0.5. As a result, our empirical data has enough convergent validity. Table 2 has these particulars.

Table 2. Reliability and Convergent Validity

Construct	**Cronbach Alpha**	**rho_a**	**rho_c**	**AVE**
Awareness of Air Quality Issues	0.869	0.881	0.910	0.717
Effort Expectancy	0.795	0.797	0.880	0.710
Facilitating Conditions	0.821	0.832	0.882	0.652
Perceived Environmental Impact	0.912	0.914	0.935	0.741
Performance Expectancy	0.885	0.889	0.916	0.685
Social Influence	0.905	0.921	0.929	0.724
Trust in Technology	0.899	0.907	0.930	0.767
Use Behavior	0.909	0.910	0.932	0.734

4.3. Discussion

This study employed the Structural Equation Modeling (SEM) approach, and SmartPLS version 4 was used to analyze the data. Table 3 displays the findings following the gathering and analysis of data.

Table 3. Structural Model Measurement of acceptance and use of AI Air Quality System

Hypothesis	**Building relationships**	**T-stats**	**P-value**
H1	Awareness of Air Quality Issues → Effort Expectancy	1.080	0.280
H2	Effort Expectancy → Use Behavior	1.190	0.234
H3	Facilitating Conditions → Use Behavior	3.327	0.001
H4	Perceived Environmental Impact → Social Influence	17.434	0.000
H5	Performance Expectancy → Use Behavior	2.168	0.030
H6	Social Influence → Use Behavior	4.016	0.000
H7	Trust in Technology → Effort Expectancy	6.340	0.000

The analysis findings of the inferred connections between the study hypothesized links and the acceptance and implementation of the AI Air Quality System are shown in Table 3. This table includes the tested hypotheses, predicted relationships between the variables (such as Awareness of Air Quality Issues Related to Effort Expectancy), the t statistic, which quantifies the discrepancy between the observed value and what was predicted by the hypothesis, and the p-value, which denotes statistical significance. The structural model measurement findings demonstrate that some ideas, such as the connections between social influence and use behavior and between facilitating conditions and use behavior, have a significant t-value (p-value 0.05). Low p-values for additional associations also indicate statistical significance and support the study tested assumptions.

Table 4. Working hypothesis testing results

Hypothesis	**Description**	**Results**
H1	Increased user awareness of air quality issues is positively associated with performance expectations in the context of AI Air Quality Systems, indicating that understanding environmental impacts can drive expectations of the technology performance.	Not supported
H2	Lower effort expectations regarding the AI Air Quality System could inhibit usage behavior, indicating that perceived ease of use is essential in technology adoption.	Not supported
H3	Facilitating condition factors, such as resource availability and support, positively impact AI Air Quality System usage behavior, suggesting that a supportive environment can stimulate users to utilize the technology more actively.	Supported

H4	User perceptions of positive environmental impacts influence social influence, illustrating that individual views of positive impacts can affect results from the surrounding social environment.	Supported
H5	Expectations of the performance of AI technology in addressing air quality issues influence usage behavior, reflecting the importance of belief in the benefits of using the technology.	Supported
H6	Social influence positively impacts the usage behavior of the AI Air Quality System, indicating that the views and beliefs of the user's social environment can influence the user intentions and actions regarding the technology.	Supported
H7	The level of user trust in AI technology positively affects performance expectations, indicating that trust in the capabilities of technology is a factor that affects user expectations of the performance of the technology.	Supported

The findings from this study testing of the working hypotheses are shown in Table 4. A summary of the test results for each hypothesis is included in this table. Each hypothesis is listed in the column titled "Hypothesis". followed by a detailed explanation in the column titled "Description", and finally, the relevant statistical test results in the column titled "Results".

To begin with, the hypothesis (H1), which explores the relationship between increased user awareness of air quality issues and performance expectations in the AI Air Quality System, did not receive significant statistical support. This suggests that understanding environmental impacts does not always directly shape expectations of technology performance.

Moving on, hypothesis (H2), which suggests that lower effort expectations may hinder usage behavior for the AI Air Quality System, also failed to reach statistical significance. This implies that the perceived ease of use of this technology is not currently a decisive factor in adoption. By contrast, the third hypothesis (H3) was strongly supported, indicating that factors such as resource availability and support positively influence users willingness to engage with the technology. This finding highlights how a well-supported environment encourages greater adoption and usage.

Shifting focus to the hypothesis (H4), which examines the connection between users perceptions of environmental impact and social influence, the results demonstrate strong statistical support. This suggests that when individuals perceive a positive environmental impact, they are more likely to be influenced by their social surroundings in adopting the technology. Similarly, the hypothesis (H5), which investigates the relationship between performance expectations and usage behavior, was also supported. The findings confirm that higher expectations of a technology ability to address air quality issues lead to increased usage.

Looking further, the hypothesis (H6) underscores the role of social influence in shaping usage behavior. The results indicate that thoughts and beliefs influenced by social environments strongly impact individuals intentions to adopt and use the technology.

Lastly, the hypothesis (H7), which explores the link between user trust in AI technology and performance expectations, received significant statistical backing. This implies that a strong belief in the reliability and capabilities of AI technology plays a crucial role in shaping users' expectations of its performance.

5. MANAGERIAL IMPLICATIONS

The findings of this study highlight important considerations for policymakers, technology developers, and environmental practitioners in promoting the adoption of AI-based Air Quality Systems. Ensuring proper infrastructure and technical support is essential, as facilitating conditions significantly impact user adoption. Building public awareness and trust is also crucial, as confidence in AI systems can be strengthened through clear communication about reliability, data security, and environmental benefits. Additionally, social influence plays a key role in adoption, suggesting that collaboration with influencers, environmental groups, and academic institutions can encourage wider acceptance.

Optimizing system performance and user experience is another key factor, as users are more likely to adopt technology that provides accurate real-time monitoring and actionable insights. While ease of use was not a primary factor in adoption, designing an intuitive and mobile-friendly system can still improve accessibility. Policymakers should also consider integrating AI-driven monitoring into environmental regulations to enhance decision-making and pollution control. Furthermore, continuous collaboration between industry, government, and academia can drive innovation and ensure that AI solutions are tailored to real-world needs. By applying these insights, stakeholders can develop more effective strategies for AI adoption in air quality management, ultimately contributing to sustainability and better environmental outcomes.

6. CONCLUSION

This study has thoroughly looked into the elements that influence the acceptance and use of artificial intelligence (AI) technology to enhance the quality of air quality systems. The presented assumptions have been examined using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, and the findings offer valuable information about how AI technology is adopted in complicated global air pollution concerns.

In this context, the hypotheses regarding the positive impact of user awareness on air quality issues (H1) and the negative impact of effort expectations (H2) did not receive significant statistical support. In contrast, the hypotheses linking facilitating conditions (H3), user perceptions of environmental impact (H4), performance expectations (H5), social influence (H6), and user trust in AI technology (H7) were strongly supported through data analysis. These findings confirm that factors such as enabling conditions, positive perceptions of environmental impact, technology performance expectations, and level of trust in technology play a central role in shaping the adoption behavior of AI technology to address air quality issues.

In essence, the main conclusion that can be drawn is that the adoption of Artificial Intelligence Technology within the scope of Air Quality Systems has a strong basis in factors such as environmental perception, performance expectation, social influence, and technology trust. Nonetheless, user awareness of air quality issues and effort expectations have been consistent determinants in adopting this technology. These results drive the direction of strategic guidance in developing promotional efforts, implementation, and cross-sector cooperation in addressing air pollution challenges through the utilization of Artificial Intelligence Technology. In line with the global agenda towards sustainability and environmental improvement, this research provides a deeper understanding of the factors that shape the adoption of AI technology to improve air quality holistically.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: TS; Methodology: DJ; Software: BT; Validation: TS and DJ; Formal Analysis: VA and MA; Investigation: TS; Resources: DJ; Data Curation: DJ; Writing Original Draft Preparation: YS and HK; Writing Review and Editing: BT and VA; Visualization: DJ; All authors, TS, DJ, BT, VA, and MA, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

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

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

7.5. 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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