The Study of Various Aspects of User Perception on the Mobile Application of AIoT-Based Air Quality Monitoring and Prediction for $PM_{2.5}$

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Abstract: This research investigates the key factors that affect user satisfaction with the "AIoT-based Air Quality Monitoring System for Real-time PM2.5 Prediction in Urban Environments" mobile application. Conducted in the Nong Khaem District of Bangkok, the study employs a quantitative research methodology with a sample of 411 respondents who have used the application. The main objective was to identify the factors that influence user satisfaction.

The study's conceptual framework categorizes 17 independent variables into four primary criteria: Core Functionality & Data Reliability, Information & Presentation Quality, Actionable Insights & User Impact, and User Experience & Social Impact.

Data analysis, which employed descriptive statistics and multiple regression, revealed that respondents generally reported high satisfaction with the system, with a mean satisfaction score of 4.34 (SD = 0.74). The multiple regression model demonstrated a strong fit (R-squared = 0.7909), indicating that the four groups of variables explain a significant portion of the variance in user satisfaction.

In conclusion, the research emphasizes the importance of a well-designed mobile application that not only provides accurate and reliable data but also effectively communicates information through clear visuals, offers actionable advice for personal protection, and ensures a positive overall user experience. The findings present valuable insights for developers and policymakers aiming to enhance the effectiveness and user adoption of environmental monitoring technologies in urban areas.

Keywords: AIoT, $PM_{2.5}$, Multiple regression model, user experience, AQI

1. Introduction

Air pollution, specifically fine particulate matter ($PM_{2.5}$) with a diameter of 2.5 micrometers or less, poses a significant health hazard in urban environments worldwide [1]. The unfavorable health consequences associated with $PM_{2.5}$ exposure [2], ranging from respiratory infections to cardiovascular crises, necessitate the development of effective monitoring and prediction systems to mitigate these risks. Conventional air quality monitoring methods [3] often rely on fixed stations, which may not capture the spatial and temporal variability of pollution within a city. To address this limitation, combining Artificial Intelligence (AI) with the Internet of Things (IoT) and developing AIoT systems offers a profitable approach for real-time, localized air quality monitoring and forecasting. This study, detailed by Otanasap et al. (2025) [1], focuses on developing an AIoT-based air quality monitoring and forecasting system designed explicitly for $PM_{2.5}$ prediction in metropolitan atmospheres. The system is designed to empower users with timely warnings through a mobile application, enabling them to take proactive measures to safeguard their health. This research contributes to the growing field of intelligent environmental monitoring by leveraging AI's capabilities for data analysis and prediction, coupled with the widespread connectivity of IoT devices. It seeks to enhance the understanding and management of urban air quality.

2. Literature Review

2.1 The development of AIoT-based air quality monitoring systems in urban areas, such as the Nong Khaem district in Bangkok, is driven by the growing demand for accurate, real-time air quality information, particularly $PM_{2.5}$ levels. The work of Otanasap et al. [1] highlights the system's potential for real-time predictions and user alerts via a mobile application. Understanding user perspectives and assessing effectiveness requires examining existing literature on air quality monitoring, user perceptions, and the role of AIoT.

(1) AIoT in Environmental Monitoring: The integration of Artificial Intelligence (AI) with the Internet of Things (IoT) enables the collection of real-time environmental data and the analysis of this data, allowing for dynamic air quality management beyond traditional monitoring methods [4] [5][6][7].

(2) $PM_{2.5}$ Prediction: Accurate prediction of $PM_{2.5}$ levels is crucial for mitigating health risks. Techniques like time series analysis and Random Forest algorithms have been applied for this purpose, as demonstrated by Otanasap et al. (2025) [1][8][9].

(3) User Perception: The success of monitoring systems relies heavily on user interaction, clarity of information, and the user-friendliness of the interface [1].

(4) Mobile Applications: Mobile apps act as the primary means of delivering air quality information to the public. Their design and usability are vital for user engagement [1].

Explorations into innovative environments for air quality management, as referenced by Schieweck et al. (2018) [10], have set the stage for broader applications in urban settings. The efficacy of the AIoT system by Otanasap et al. (2025) [1] hinges on accurate predictions, which can be evaluated against various machine learning models [11].

Ultimately, user adoption of these technologies is essential to their success, and insights from mobile health applications provide valuable guidance for effective engagement [12][13].

2.2 This study investigates user perception of the "AIoT-based Air Quality Monitoring System for Real-time $PM_{2.5}$ Prediction in Urban Environments" [14]. The research framework is built upon established theories in information systems success, technology acceptance, and health behavior. This review synthesizes literature to develop the theoretical foundation for the 17 variables, which are organized into four primary constructs: (1) Core Functionality & Data Reliability, (2) Information & Presentation Quality, (3) Actionable Insights

& User Impact, and (4) User Experience & Social Impact.

2.2.1 Core Functionality & Data Reliability

This construct (Variables X_1-X_4) assesses the fundamental performance of the system. It is grounded in technology acceptance and information systems (IS) success models.

1) Core Functionality (X_1, X_3): The usefulness of $PM_{2.5}$ forecasts for planning (X_1) and the adequacy of data update frequency (X_3) are direct indicators of Performance Expectancy, a key concept in the Unified Theory of Acceptance and Use of Technology (UTAUT) [15]. Performance Expectancy is defined as the extent to which an individual believes that using the system will help them improve their job or daily life performance [16]. In the context of a $PM_{2.5}$ app, "performance" refers to the user's ability to plan daily activities and reduce health risks.

2) Data Reliability (X_2, X_4): The perceived accuracy of forecasts (X_2) and the system's consistency (X_4) are crucial components of System Quality and Information Quality, which are essential dimensions of the DeLone & McLean (D&M) IS Success Model. In the context of mHealth, ensuring system reliability and data accuracy is vital. If users view the data as inaccurate (X_2) or the system as unreliable (X_4), their trust in the system diminishes, resulting in decreased usage. Therefore, these variables are fundamental to user acceptance.

2.2.2 Information and Presentation Quality

This construct (Variables X_5-X_8) assesses how effectively information is communicated to the user, focusing not just on its existence but also on its cognitive accessibility. This closely aligns with the Information Quality dimension of the DeLone and McLean Information Systems Success Model.

1) Understandability (X_5, X_6): The D&M model emphasizes that information must be clear to be effective. This involves the clarity of index values (X_5) and the effectiveness of visual aids, such as charts and colors (X_6). In health communication, this concept is connected to eHealth Literacy, which refers to users' ability to find, understand, and evaluate health information from electronic sources [17]. Effective data visualization (X_6) is crucial for communicating complex risks, such as Air Quality Index (AQI) levels, to a general audience.

2) Communication Effectiveness (X_7, X_8): The system's capability to communicate potential changes (X_7) relates to the "timeliness" and "relevance" aspects of Information Quality. Offering detailed information about $PM_{2.5}$ sources (X_8) increases the "completeness" of the data, providing users with a deeper understanding of their environment and encouraging greater engagement.

2.2.3: Actionable Insights and User Impact

This construct (Variables X_9-X_{12}) evaluates the system's effectiveness in converting data into actionable insights for users and the perceived advantages, both of which are fundamental aims of health information systems. Theories of health behavior significantly influence this area.

1) Cues to Action (X_9, X_{10}): The Health Belief Model (HBM) offers a solid framework for understanding this construct [18]. Timely warnings and alerts (X_9) serve as a "Cue to Action," an essential element of the HBM that initiates the decision-making process for health protection. Information about potential health risks (X_{10}) directly addresses two other HBM constructs: "Perceived Susceptibility" (the belief in the likelihood of acquiring a condition) and "Perceived Severity" (the belief in the seriousness of a condition).

2) Perceived Benefits and Behavior Change (X_{11}, X_{12}): The belief that the system provides protection for oneself and one's family (X_{11}) serves as a direct measure of "Perceived Benefits" [18]. Additionally, the system's positive impact on daily decision-making (X_{12}) is a tangible outcome of this belief. This aligns with the objectives of mHealth interventions, which aim to promote positive behavior changes and enhance health outcomes [19].

2.2.4 User Experience & Social Impact

This final construct (Variables X_{13}-X_{17}) focuses on the system's usability and its impact on individual and community awareness, drawing from usability and social diffusion theories.

1) User Experience (X_{13}) refers to how easy it is to use the mobile application interface. This ease of use is a direct measure of Effort Expectancy from the Unified Theory of Acceptance and Use of Technology (UTAUT), which indicates the level of comfort users experience when interacting with the system [17]. Additionally, this concept aligns with Perceived Ease of Use from the original Technology Acceptance Model (TAM), which is a key factor influencing user adoption and satisfaction [20].

2) Social and Awareness Impact (X_{14}, X_{15}, X_{16}, X_{17}): This group of variables assesses the broader influence of the system.

2.1) Recommendation of the system to others (X_{15}) serves as an indicator of user satisfaction. It is associated with Social Influence (as outlined in the UTAUT model) and the Diffusion of Innovations theory, wherein peer recommendations are a crucial avenue for adoption [21].

2.2) Providing users with more information (X_{14}) and increasing their awareness of pollution (X_{16}) are indicators of the system's success as an educational and awareness tool.

2.3) The belief that the system can enhance the community environment (X_{17}) reflects users' perceptions of its collective benefits and contributions to social good, which is a strong motivator for sustained engagement [22].

3. Materials and Methods

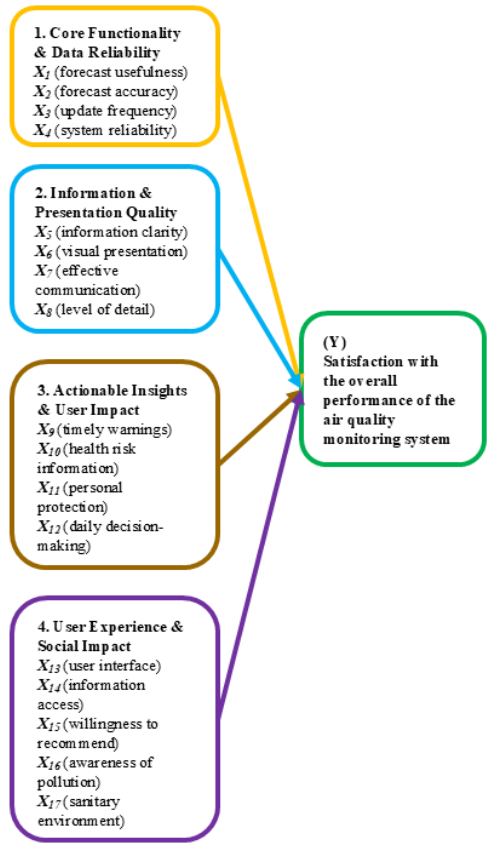

Fig. 1 Research Framework

This research aims to examine the factors affecting users' perceptions of an IoT-based air quality monitoring and forecasting system for $PM_{2.5}$ in urban areas, focusing on a case study in Nong Khaem District, Bangkok. To achieve this research objective, the researcher employed a quantitative research method, using a questionnaire as the data collection tool. The details of the research methodology are as follows:

1) Research framework

2) Research hypothesis
3) Population group definition and sample selection
4) Data sources used in the research
5) Research instruments
6) Testing the research instruments
7) Data collection
8) Data analysis and hypothesis testing

3.1 Research Framework

The researcher has selected the variables to be studied to create a research conceptual framework, as shown in Figure 1.

3.2 Research Hypothesis

This study has a total of 17 related variables to test 4 variable groups according to the research conceptual framework, with the following variable groups:

1) Core Functionality & Data Reliability
2) Information & Presentation Quality
3) Actionable Insights & User Impact
4) User Experience & Social Impact

3.3 Population group definition and sample selection

1) Population used in the research

The population in this research comprises individuals aged 15 years and over who live or work in Nong Khaem District, Bangkok, and who have used the application system before. According to the census, the population of Nong Khaem District is 155,124, but because of a hidden population of residents and workers, the actual number is unknown. The researcher therefore found the sample size by calculating with the Cochran formula [23] With a 95% confidence level as follows:

$$n = \frac{Z^2 * p * (1-p)}{e^2} \qquad (1)$$

Where ***n*** represents the sample size, ***p*** represents the percentage to be randomly selected from the entire population (***p*** = 0.5) ***Z*** represents the confidence level, set to 95% (equal to 1.96), and ***e*** represents the percentage of error (***e*** = 0.05) from the random sampling.

The ***P*** value must be set to at least 50%. The sample size is at a reliable level. Therefore, to ensure the number distribution is an integer and prevent errors in answering the questionnaire, 411 questionnaires are distributed.

2) Sample Selection Method

This research used non-probability purposive sampling to select only those who had tried the developed app, distributing 411 online Google Form questionnaires.

3.4 Data sources used in the research

1) Primary data sources, the researcher used a quantitative data collection method with an online questionnaire of 411 samples to analyze the data.

2) Secondary data sources, the researcher studied and found information from academic articles and information generally published from reliable sources, both from journals and online databases, both domestic and international.

3.5 Research instruments

This research is quantitative, using a questionnaire to collect data. The questionnaire consists of closed-ended questions about factors affecting the perception of the application presented.

The criteria for scoring the level of opinions on the use of the presented application used a 5-level Likert scale, with values ranging from strongly agree to disagree strongly.

To evaluate the level of opinions on the perception of the use of the presented application, a formula was used to calculate the width of each level according to the concept of Paul E. Green and Donald S. Tull [24], which was calculated as follows:

$$CIW = \frac{(HV - LV)}{NC} \qquad (2)$$

= (5-1)/5

= 0.8

CIW: Class Interval Width HV: Highest Value
NC: Number of Classes LV: Lowest Value

3.6 Testing the research instruments

The researcher tested the validity and reliability of the questionnaire used in the research as follows:

1) Study the guidelines and collect data from related research to be an example for creating the questionnaire.

2) Present the developed questionnaire to 3 experts to check the language accuracy and content accuracy to improve the questionnaire to be accurate and complete according to the objectives of this research study.

3) Test the questionnaire with 20 experimental groups and adjust it according to the suggestions of the experimental group.

4) Use the revised questionnaire with 411 samples.

3.7 Data collection

In this research, the data were collected by online questionnaires. The researcher selected only complete questionnaires from the data, converted the values into codes, and analyzed them using Google Spreadsheet and XLMiner Analysis ToolPak.

3.8 Data analysis and hypothesis testing

The details of the statistics used in the processing are as follows:

1) Data analysis using descriptive statistics, to analyze the demographic characteristics of the sample group, consisting of age, gender, education level, occupation, reasons for staying in Nong Khaem District, duration of stay in Nong Khaem District, with the statistical values used being frequency and percentage, and to analyze data on factors affecting the perception of app usage presented by the statistical values used being the mean and standard deviation.

2) Data analysis using inferential statistics

Two-step statistical analysis tools were used to test the research hypothesis as follows:

Step 1: Factor analysis of variables or group variables that are related together. Variables within the same group will have a strong relationship; the relationship may be in the same or opposite direction. As for variables across groups, there will be no relationship or only a very weak one.

Step 2: The multiple correlation coefficient analysis to analyze the independent variables or factors that affect the perception of the use of the presented **17** variables to see how much they are related and in which direction they are related, including finding the relationship of these factors with the perception of the use of the presented applications. Based on the descriptions provided, the independent variables can be grouped into the following main criteria related to a $PM_{2.5}$ prediction mobile application.

Group 1. Core Functionality & Data Reliability: This group includes variables that assess the application's primary purpose: to provide accurate, up-to-date, and reliable information.

X_1**:** The $PM_{2.5}$ forecast displayed by the system at levels 1, 3, 6, 12, and 24 hours in advance helps plan your daily activities.

X_2**:** The forecast of air quality and future $PM_{2.5}$ levels of the system can be accurately predicted.

X_3**:** The frequency of $PM_{2.5}$ level updates that the system can provide (every 1 hour) is sufficient for your information.

X_4**:** The system is reliable in providing consistent air quality information.

Group 2. Information & Presentation Quality, this group focuses on how the information is communicated to the user, including ease of understanding and clarity.

X_5**:** The information that the system displays in advance regarding the AQI $PM_{2.5}$ index values in the Nong Khaem District area is easy to understand.

X_6**:** The presentation of air quality data in visual form (e.g., charts, colors) is clear and provides sufficiently useful information.

***X_7*:** The system can effectively communicate potential changes in air quality.

***X_8*:** The level of detail provided regarding the sources or factors affecting $PM_{2.5}$ is helpful.

Group 3. Actionable Insights & User Impact: This group includes variables that assess the application's ability to help users make informed decisions and take protective actions.

***X_9*:** The warnings or alerts the system provides when $PM_{2.5}$ levels are high are timely, and what you want from the system.

***X_{10}*:** The system can provide sufficient information on the potential health risks from different $PM_{2.5}$ levels.

***X_{11}*:** The system helps you protect yourself and your family from air pollution.

***X_{12}*:** The system has an impact on your daily decision-making about outdoor activities, which is a positive impact (making you make better decisions about activities).

Group 4. User Experience & Social Impact, this group encompasses factors related to the overall user experience, including ease of use, awareness, and the user's willingness to recommend the application to others.

***X_{13}*:** The interface or user interface of the mobile application is easy to use.

***X_{14}*:** The system helps you get more information about air quality in Nong Khaem District.

***X_{15}*:** Will recommend this air quality monitoring system to your friends and family.

***X_{16}*:** Using this system makes you more aware of $PM_{2.5}$ pollution in your neighborhood.

***X_{17}*:** This type of system can help make the living environment in your residential area more sanitary.

The multiple correlation coefficient, denoted as $R_{y.x_1.x_2.x_3.x_4}$ quantifies the linear relationship between a dependent variable Y and a set of independent variables: *Group 1* (X_1, X_2, X_3, X_4), *Group 2* (X_5, X_6, X_7, X_8), *Group 3* (X_9, X_{10}, X_{11}, X_{12}), and *Group 4* (X_{13}, X_{14}, X_{15}, X_{16}, X_{17}). The squared multiple correlation coefficient can be expressed in terms of the correlation matrix. Let R be the correlation matrix of all variables, with the dependent variable Y as the first variable and x_1, x_2, x_3, x_4 as the subsequent variables. The formula is given by:

$$R^2_{y.x_1.x_2.x_3.x_4} = 1 - \frac{|R|}{|R_{xx}|} \qquad (2)$$

where $|R|$ is the determinant of the full correlation matrix R, and $|R_{xx}|$ is the determinant of the submatrix of R containing only the correlations among the independent variables X_1, X_2, X_3, X_4.

The multiple correlation coefficient $R_{y.x_1.x_2.x_3.x_4}$ is calculated using the formula (2), where $|R|$ is the determinant of the correlation matrix of all variables and $|R_{xx}|$ is the determinant of the correlation matrix of the independent variables.

4. Results and Discussion

This section presents the results of the data analysis, including a descriptive overview of the sample demographics, a statistical summary of the dependent and independent variables, and the findings from the multiple regression analysis.

4.1 General Sample Characteristics

The study was conducted with 411 respondents in Nong Khaem District. The sample's demographic information is detailed below:

- **Age:** The largest age group was 15-24 years old (169 respondents), followed by 45-54 years (83), and 35-44 years (72).
- **Gender:** There was a higher number of male respondents (235) compared to female respondents (173).
- **Educational Level:** The majority of respondents (259) had a bachelor’s degree or were currently pursuing one, while 119 had a master’s degree or were studying for one.

• **Occupation:** The most common occupations were students (167) and educational personnel (156).
• **Reason for being in the district:** A significant portion of the sample (274 respondents) were in the Nong Khaem District for work or educational purposes.
• **Time in the District:** The most frequent response for time spent in the area was "more than 10 years" (181 respondents), followed by "1-5 years" (163).

4.2 Descriptive Statistics of Variables

The mean values for the dependent and independent variables, measured on a Likert scale from 1 (lowest) to 5 (greatest), indicate a generally high level of satisfaction and positive perception among respondents.

1) Mean Value and Standard Deviation of Each Question

The mean value represents the average score given by respondents, while the standard deviation (SD) indicates the degree of variation in the responses. A lower standard deviation suggests that most respondents had similar opinions, while a higher one indicates a wider range of views.

Dependent Variable (Y): Satisfaction with the overall performance of the air quality monitoring system is Mean: 4.34, SD: 0.74.

According to Figure 2, Independent Variables (X_1-X_4), $\boldsymbol{X_1}$ (AQI $PM_{2.5}$ information is easy to understand): Mean 4.44, SD 0.77. This variable had the highest mean, suggesting that users found the information very easy to understand and that there was strong consensus. $\boldsymbol{X_2}$ ($PM_{2.5}$ forecast is useful for planning): Mean 4.18, SD 0.79. Users generally found the forecast helpful, though opinions were slightly more varied than in X_1. $\boldsymbol{X_3}$ (Warnings are timely and desired): Mean 4.27, SD 0.79. The high mean indicates users felt the warnings were timely and desired, but the responses were slightly dispersed. $\boldsymbol{X_4}$ (Mobile application interface is easy to use): Mean 4.19, SD 0.81. Users found the interface easy to use, though opinions on this factor ranged slightly more widely.

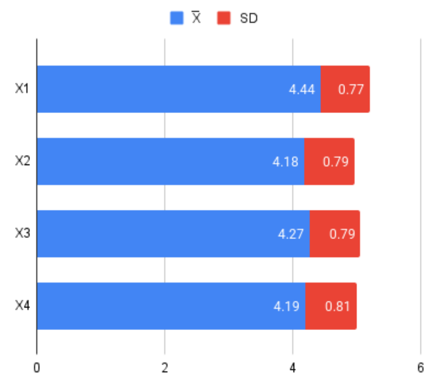

Fig 2. Independent Variables (X_1-X_4)

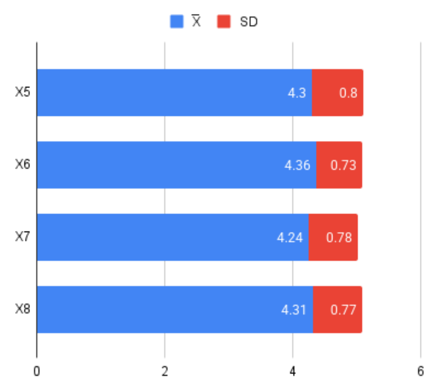

Fig 3. Independent Variables (X_5-X_8)

According to Figure 3, $\boldsymbol{X_5}$ (Sufficient health risk information): Mean 4.30, SD 0.80. The high mean indicates that users were satisfied with the amount of health risk information provided. $\boldsymbol{X_6}$ (Forecast can be accurately predicted): Mean 4.36, SD 0.73. This is one of the highest mean values, suggesting that users have strong confidence in the system's forecast accuracy. The low standard deviation shows firm agreement. $\boldsymbol{X_7}$ (Helps you get more information): Mean 4.24, SD 0.78. Users felt the system helped them get more information, though responses varied moderately. $\boldsymbol{X_8}$ (Will recommend to friends and family): Mean

4.31, SD 0.77. A high mean here indicates that users are likely to recommend the system to others.

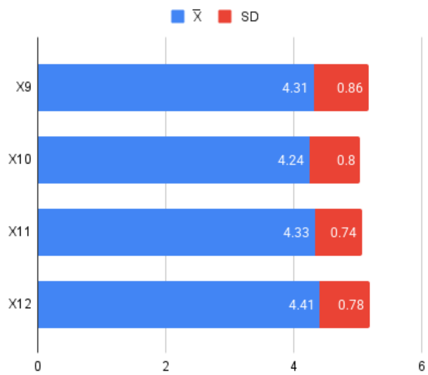

Fig 4. Independent Variables (X_9-X_{12})

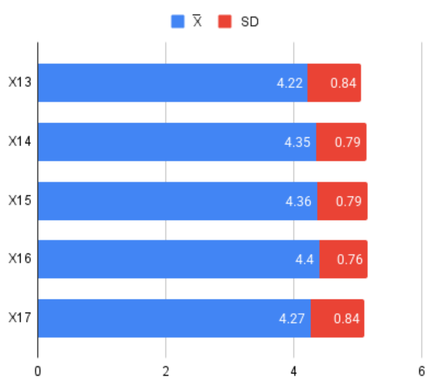

Fig 5. Independent Variables (X_{13}-X_{17})

According to Figure 4, $\boldsymbol{X_9}$ (Update frequency is sufficient): Mean 4.31, SD 0.86. The high standard deviation here indicates a broader range of opinions on whether the one-hour update frequency is adequate, despite the high mean. $\boldsymbol{X_{10}}$ (System is reliable): Mean 4.24, SD 0.80. Users generally found the system reliable, with a moderate spread in responses. $\boldsymbol{X_{11}}$ (Visual data presentation is clear): Mean 4.33, SD 0.74. This high mean and low standard deviation shows strong agreement that the visual data presentation is clear. $\boldsymbol{X_{12}}$ (Helps protect yourself and family): Mean 4.41, SD 0.78. This is one of the highest mean scores, indicating that users feel the system is very effective in helping them protect their families from pollution.

According to Figure 5, $\boldsymbol{X_{13}}$ (Can effectively communicate changes): Mean 4.22, SD 0.84. While the mean is high, the standard deviation is also high, indicating varied opinions on the effectiveness of communicating changes. $\boldsymbol{X_{14}}$ (Makes you more aware of pollution): Mean 4.35, SD 0.79. Users strongly feel that the system increases their awareness of $PM_{2.5}$ pollution. $\boldsymbol{X_{15}}$ (Detail on sources is helpful): Mean 4.36, SD 0.79. A very high mean score suggests that users found the detailed information about pollution sources helpful. $\boldsymbol{X_{16}}$ (Impact on daily decision-making): Mean 4.40, SD 0.76. This high mean indicates that the system has a very positive impact on users' daily decisions about outdoor activities.
$\boldsymbol{X_{17}}$ (Helps make living environment more sanitary): Mean 4.27, SD 0.84. While the average score is high, the high standard deviation suggests a broader range of opinions on whether the system improves the sanitary conditions of their living environment.

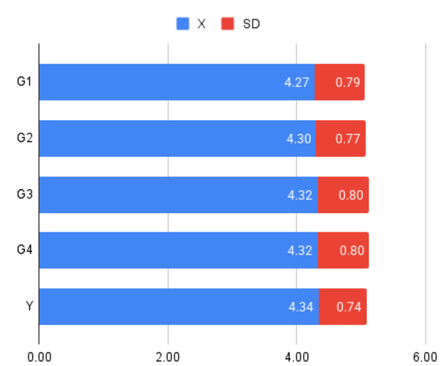

Fig 6. Independent Variable Groups (G_1-G_4) and Dependent Variable (Y)

According to Figure 6, the mean satisfaction with the air quality monitoring system ***(Y)*** was 4.34, with a standard deviation of 0.74. The average scores for the independent variable groups were also consistently high:

G_1: Core Functionality & Data Reliability: Mean of 4.27 (SD = 0.79).

G_2: Information & Presentation Quality: Mean of 4.30 (SD = 0.77).

G_3: Actionable Insights & User Impact: Mean of 4.32 (SD = 0.80).

G_4: User Experience & Social Impact: Mean of 4.32 (SD = 0.80).

The high mean of 4.34 indicates that respondents were, on average, very satisfied with the system's overall performance. The low standard deviation suggests high agreement among users regarding their satisfaction.

4.3 The results of the multiple regression analysis

This section presents the results of the multiple regression analysis conducted on the independent variable groups to determine their influence on the dependent variable, "Satisfaction with the overall performance of the air quality monitoring system" (Y). The analysis is divided into four main sections, corresponding to each group of independent variables.

Dependent Variable (Y): Satisfaction with the overall performance of the air quality monitoring system

4.3.1 Independent Variable Group 1. Core Functionality & Data Reliability

This group includes variables that assess the application's primary purpose: to provide accurate, up-to-date, and reliable information.

According to Table 1, Core Functionality & Data Reliability, the regression model for this group of variables (X_1-X_4) yielded a **Multiple R** of 0.8092 and an **R-squared** of 0.6547. This indicates that approximately 65.47% of the variability in user satisfaction can be explained by the variables in this group. The model was found to be statistically significant, with a significance F-value of 0.

Upon examining the individual coefficients:

***X_1* (forecast usefulness)** was not a statistically significant predictor of satisfaction, as its p-value was 0.4196, which is greater than the significance level of 0.05.

***X_2* (forecast accuracy)** was a highly significant predictor, with a p-value of 0. Its positive coefficient of 0.2892 suggests that forecast accuracy strongly contributes to user satisfaction.

***X_3* (update frequency)** was also a significant predictor, with a p-value of 0.0120. The positive coefficient of 0.0971 indicates that a higher update frequency is associated with greater satisfaction.

***X_4* (system reliability)** was a highly significant predictor, with a p-value of 0. The large positive coefficient of 0.4333 suggests that a reliable system is the most influential factor in this group, leading to higher user satisfaction.

4.3.2 Independent Variable Group 2. Information & Presentation Quality

This group focuses on how the information is communicated to the user, including ease of understanding and clarity.

According to Table 2, Information & Presentation Quality, the regression analysis for this group (X_5 to X_8) revealed a strong model fit, with a **Multiple R** of 0.8982 and an **R-squared** of 0.8068, indicating that these variables can explain 80.68% of the variability in satisfaction. The model was statistically significant with a **Significance F of 0.** All variables in this group were found to be statistically significant:

***X_5* (information clarity)** had a p-value of 0.0277, indicating it is a significant predictor.

***X_6* (visual presentation)** was highly significant, with a p-value of 0. Its positive coefficient of 0.2016 shows a clear link between a good visual interface and increased satisfaction.

***X_7* (effective communication)** was highly significant with a p-value of 0. The coefficient of 0.4479 suggests it is a powerful predictor of user satisfaction.

***X_8* (level of detail)** was also highly significant, with a p-value of 0. The positive coefficient of 0.2841 indicates that providing helpful information about $PM_{2.5}$ factors positively influences satisfaction.

4.3.3 Independent Variable Group 3. Actionable Insights & User Impact

This group includes variables that measure the application's ability to help users make informed decisions and take protective actions.

According to Table 3, Actionable Insights & User Impact, the regression model for this group (X_9-X_{12}) was significant, with a ***Multiple R*** of 0.8630 and an ***R-squared*** of 0.7448. This means that these factors can explain 74.48% of the variability in satisfaction. The model's Significance ***F*** was 0. The analysis of individual predictors showed mixed results:

***X_9* (timely warnings)** was not statistically significant, with a p-value of 0.9547. This suggests that the timeliness of warnings, on its own, does not significantly predict satisfaction.

***X_{10}* (health risk information)** was a highly significant predictor, with a p-value of 0. The strong positive coefficient of 0.3505 indicates that providing information on health risks is a key driver of satisfaction.

***X_{11}* (personal protection)** was also highly significant, with a p-value of 0. With a coefficient of 0.4747, it had the most substantial positive impact on satisfaction within this group, highlighting the importance of the app helping users protect themselves and their families.

***X_{12}* (daily decision-making)** was a statistically significant predictor, with a p-value of 0.0017. Its positive coefficient of 0.1104 indicates that the system's impact on better decision-making is also a positive factor for satisfaction.

Table 1 Core Functionality & Data Reliability

Regression Statistics	
Multiple R	0.8092
R Square	0.6547
Adjusted R Square	0.6513
Standard Error	0.4384
Observations	411

ANOVA	*df*	*SS*	*MS*	*F*	*Sig. F*
Regression	4	147.9629	36.9907	192.4740	0
Residual	406	78.0274	0.1922		
Total	410	225.9903			

	Coefficients	*Std. Err.*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.7494	0.1417	5.2905	0.0000	0.4710	1.0279
X_1	0.0335	0.0415	0.8079	0.4196	-0.0480	0.1151
X_2	0.2892	0.0397	7.2913	0.0000	0.2113	0.3672
X_3	0.0971	0.0385	2.5221	0.0120	0.0214	0.1728
X_4	0.4333	0.0403	10.7570	0.0000	0.3541	0.5125

Table 2 Information & Presentation Quality

Regression Statistics	
Multiple R	0.8982
R Square	0.8068
Adjusted R Square	0.8049
Standard Error	0.3279
Observations	411

ANOVA	*df*	*SS*	*MS*	*F*	*Sig. F*
Regression	4	182.3402	45.5850	423.9976	0
Residual	406	43.6501	0.1075		
Total	410	225.9903			

	Coefficients	*Std. Err.*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.1013	0.1112	0.9112	0.3627	-0.1173	0.3199
X_5	0.0553	0.0250	2.2091	0.0277	0.0061	0.1044
X_6	0.2016	0.0364	5.5339	0.0000	0.1300	0.2732
X_7	0.4479	0.0357	12.5382	0.0000	0.3777	0.5181
X_8	0.2841	0.0288	9.8551	0.0000	0.2274	0.3407

Table 3 Actionable Insights & User Impact

Regression Statistics	
Multiple R	0.8630
R Square	0.7448
Adjusted R Square	0.7423
Standard Error	0.3769
Observations	411

ANOVA	*df*	*SS*	*MS*	*F*	*Sig. F*
Regression	4	168.3259	42.0815	296.2851	0
Residual	406	57.6643	0.1420		
Total	410	225.9903			

	Coefficients	*Std. Err.*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.3185	0.1222	2.6070	0.0095	0.0783	0.5587
X_9	-0.0019	0.0332	-0.0568	0.9547	-0.0671	0.0634
X_{10}	0.3505	0.0333	10.5095	0.0000	0.2849	0.4160
X_{11}	0.4747	0.0387	12.2628	0.0000	0.3986	0.5508
X_{12}	0.1104	0.0350	3.1557	0.0017	0.0416	0.1792

Table 4 User Experience & Social Impact

Regression Statistics	
Multiple R	0.8319
R Square	0.6921
Adjusted R Square	0.6883
Standard Error	0.4145
Observations	411

ANOVA	*df*	*SS*	*MS*	*F*	*Sig. F*
Regression	5	156.4085	31.2817	182.0748	0
Residual	405	69.5818	0.1718		
Total	410	225.9903			

	Coefficients	*Std Err.*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.3514	0.1351	2.6009	0.0096	0.0858	0.6170
X_{13}	0.1797	0.0337	5.3259	0.0000	0.1134	0.2461
X_{14}	0.1313	0.0426	3.0850	0.0022	0.0476	0.2149
X_{15}	0.2541	0.0480	5.2929	0.0000	0.1598	0.3485
X_{16}	0.2288	0.0392	5.8361	0.0000	0.1517	0.3059
X_{17}	0.1269	0.0340	3.7339	0.0002	0.0601	0.1936

Table 5 Group Analysis

Regression Statistics	
Multiple R	0.8893
R Square	0.7909
Adjusted R Square	0.7888
Standard Error	0.3412
Observations	411

ANOVA	*df*	*SS*	*MS*	*F*	*Sig. F*
Regression	4	178.7360	44.6840	383.9167	0
Residual	406	47.2543	0.1164		
Total	410	225.9903			

	Coefficients	*Std. Err.*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.1583	0.1169	-1.3540	0.1765	-0.3882	0.0715
Group 1.	-0.0447	0.0569	-0.7845	0.4332	-0.1566	0.0673
Group 2.	0.6995	0.0623	11.2239	0.0000	0.5770	0.8220
Group 3.	0.1791	0.0644	2.7828	0.0056	0.0526	0.3057
Group 4.	0.2097	0.0643	3.2603	0.0012	0.0832	0.3361

4.3.4 Independent Variable Group 4. User Experience & Social Impact

This group encompasses factors related to the overall user experience, including ease of use, awareness, and the user's willingness to recommend the application to others.

According to Table 4.3.4 User Experience & Social Impact, this group (X_{13} to X_{17}) showed a ***Multiple R*** of 0.8319 and an ***R-squared*** of 0.6921, indicating that these variables explain 69.21% of the variability in satisfaction. The model was statistically significant with a ***Significance F*** of 0.

All five variables in this group were statistically significant predictors of satisfaction:

X_{13} **(user interface)** had a p-value of 0, indicating a strong relationship.

X_{14} **(information access)** had a p-value of 0.0022, confirming its significance.

X_{15} **(willingness to recommend)** was highly significant with a p-value of 0. The coefficient of 0.2541 indicates a strong association between user satisfaction and willingness to recommend the system to others.

X_{16} **(awareness of pollution)** had a p-value of 0, indicating a highly significant relationship.

X_{17} **(sanitary environment)** was significant with a p-value of 0.0002.

4.3.5 Summary of Group Analysis

- Independent Variable Group 1. Core Functionality & Data Reliability
- Independent Variable Group 2. Information & Presentation Quality
- Independent Variable Group 3. Actionable Insights & User Impact
- Independent Variable Group 4. User Experience & Social Impact
- Dependent Variable (Y): Satisfaction with the overall performance of the air quality monitoring system

A final regression model combining all four groups as independent variables was also conducted, with "Satisfaction" as the dependent variable. The model was significant, with a ***Multiple R of 0.8893*** and an ***R-squared of 0.7909***. This suggests that the combination of these four criteria explains a substantial portion of the variability in user satisfaction with the mobile application. The results of this final model showed that three of the four groups were statistically significant predictors of satisfaction:

1) Group 2. Information & Presentation Quality was a highly significant predictor (p-value = 0) with the largest coefficient (0.6995), indicating the most important positive impact on user satisfaction.

2) Group 3. Actionable Insights & User Impact was also a significant predictor, with a p-value of 0.0056.
3) Group 4. User Experience & Social Impact was a significant predictor (p-value = 0.0012).
4) Group 1. Core Functionality & Data Reliability was not a significant predictor in this combined model (p-value = 0.4332). This suggests that while individual variables within this group (such as X2 and X4) are essential, when grouped together, this criterion is not a significant standalone predictor of satisfaction compared to the others.

5. Conclusion and Future Work

This study presents a framework to assess user perceptions of an AIoT-based air quality monitoring and prediction system. By integrating 17 key variables from information systems (D&M, UTAUT) and health behavior (HBM), we identify the primary drivers of user satisfaction, ranging from system reliability to its influence on personal decisions and social awareness.

The findings validate the system developed by Otanasap et al. (2025) [14] and provide a roadmap for future enhancements and research. Here are suggestions for future work, categorized by key constructs:

1) Core Functionality & Data Reliability: Enhance Predictive Accuracy, Explore advanced machine learning techniques to improve long-range predictions. Integrate Diverse Data Sources, Incorporate additional data like real-time traffic and localized weather patterns for more accurate air quality predictions.

2) Information & Presentation Quality: Personalized Visualization, Conduct A/B testing on various visualizations to find the most effective formats for different user segments. Dynamic Source Attribution: Develop features that provide real-time insights into pollution sources, such as "high traffic" or "agricultural burning.”

3) Actionable Insights & User Impact: Longitudinal Behavior Study: Conduct long-term studies to measure the system's impact on user behavior and health. Smart Device Integration: Integrate with smart home devices and wearables to create an automatic response system for air quality alerts.

4. User Experience & Social Impact: Qualitative Deep Dive, Supplement quantitative findings with interviews and focus groups to understand user motivations and experiences. Community Policy Impact: Examine the system's role in local advocacy and policy-making to empower community engagement on air quality issues. Broader Demographic and Geographic Studies: Replicate the study in various settings to explore the differences in user perceptions across demographics and locations.

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