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Perceived Accuracy and User Behavior: Exploring the Impact of AI-Based Air Quality Detection Application (AIKU)

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ABSTRACT

The accuracy of air quality detection is a crucial aspect influencing user trust and satisfaction with artificial intelligence (AI) based air quality detection applications. However, only a few studies have tested the effect of the accuracy of AI-based quality detection on users' acceptance and use of these applications. This study aims to fill this gap by addressing the impact of perceived accuracy on behavioral intention and behavior using the AIKU application. This research uses a quantitative approach with the online survey method, distributed in January 2023 - February 2023 to AIKU users. Valid data were 287 respondents from 317 who were received and analyzed using partial least squares structural equation modeling (PLS-SEM). This study uses a modified technology acceptance (TAM) model by adding perceived intelligence as a mediating variable between perceived accuracy and usefulness. The results showed that nine hypotheses were accepted from the 13 hypotheses proposed. The results section of hypothesis testing shows that the effect of perceived AIKU application accuracy on perceived usability and ease of use is insignificant. However, these influences indirectly affect the behavioral intentions and attitudes of users. Even if users do not perceive purity as an essential factor, the user's attitude towards the application is still positive. This study makes a theoretical contribution by developing the TAM model by incorporating variables of perceived accuracy and perceived intelligence relevant to the AI-based context.

1. Introduction

Air quality is one of the crucial factors affecting human health and well-being. According to the World Health Organization (WHO), around 7 million people die each year from exposure to air pollution, both indoors and outdoors (Syuhada et al., 2023). Air pollution can also cause various respiratory, cardiovascular, and neurological diseases and increase the risk of cancer and infection (Sharma & Balyan, 2020). Therefore, monitoring and controlling air quality is one of the global priorities to protect the environment and society (Gupta et al., 2019). One way to monitor air quality is to use an air quality detection application that can be accessed via a smart device such as a smartphone or tablet (Rahardja et al., 2023). AIKU is an Artificial Intelligence-based air quality detection application that can provide information about pollutant levels in the air, such as weather levels, humidity levels, pressure, wind speed, and air pollution levels (Rahardja et al., 2023). This application can give warnings to users regarding the quality of the surrounding air and provide recommendations on ways that can be done to protect themselves from air pollution, which can be accessed by anyone who has registered on the application (Okokpujie et al., 2018). The level of accuracy of each air quality detection application can vary, and widespread use of such applications still poses various challenges.

The accuracy of air quality detection can be affected by various factors, such as data sources, analysis methods, prediction algorithms, and user interfaces (Bhalgat et al., 2019). One technology that can improve the accuracy of air quality detection is artificial intelligence (AI). AI is a branch of computer science that aims to create systems or machines that can mimic human abilities in learning, thinking, and adapting (Jentzer et al., 2023). Using machine learning or deep learning methods, AI can process air quality data from various sources, such as sensors, satellites, or monitoring stations (Lutfiani et al., 2023); AI can also make predictions or simulations about future air quality using statistical or mathematical methods (Xiang et al., 2023). In the context of this research, the main problem is how the perception of the accuracy of the AIKU application affects the Perceived Usability (user's perception of ease of use) and Perceived Ease of Use (user's perception of usability) of this application. Does the AIKU Application's perceived accuracy significantly influence users' intention to use it? (Kelly et al., 2022). This research aims to investigate the influence of the perceived accuracy of the AIKU Application on Perceived Usability and Perceived Ease of Use, as well as the user's intention to use it. This research will help understand how the perceived accuracy of AI-based air quality apps influences how users interact with those apps. In this context, perceived accuracy refers to the user's view of the extent to which the AIKU application can provide correct and reliable information about air quality (Rhee et al., 2022). The research will answer a series of research questions: 1) To what extent do users consider the AIKU Application accurate in detecting air quality?; 2) How does the perceived accuracy of the AIKU Application affect the Perceived Usability of the application? 3) How does the perceived accuracy of the AIKU application affect the Perceived Ease of Use of the application?; 4) Does the perception of the accuracy of the AIKU Application influence the user's intention to use it?; 5) Are other factors influencing the user's intention to use it?

This study uses a modified TAM model by adding perceived intelligence as a mediating variable between perceived accuracy and usefulness. Perceived intelligence is the user’s perception of how innovative the application is in doing its job (Na et al., 2022). Empirical research was involved through a survey of AIKU application users. This survey is designed to collect data about user perceptions of the accuracy of the AIKU Application, Perceived Usability, Perceived Ease of Use, and user intentions to use the application. Furthermore, statistical data analysis will test hypotheses and explain the relationship between these variables.

1.1. Artificial Intelligence-Based Approach in Air Quality Detection

Saravanan and Kumar (2021) propose a model for detecting air quality based on artificial intelligence using spatial-temporal data from the Internet of Things (IoT). They used a bidirectional recurrent neural network (Bi-RNN) to extract spatial-temporal features from high-resolution but unstable and incomplete IoT data. They also used a genetic optimization algorithm to determine the optimal parameters of the Bi-RNN model. They evaluated the performance of their model using air quality data from Delhi, India, and compared it to a unidirectional RNN model and a multiple linear regression model. They show that the Bi-RNN model can significantly improve the accuracy of air quality detection and quality monitoring. They also presented challenges and opportunities for further research, such as using multi-source data, ensemble methods, and model interpretation techniques.

1.2. Data Cleaning and Empty Data Filling in Air Quality Sensors

Ottosen and Kumar (2019) applied outlier detection methods and filled in blanks for air quality data from low-cost sensors. They applied two outlier detection methods, namely point outlier and contextual outlier methods, and five methods for filling in blank data: linear interpolation, cubic spline interpolation, seasonal decomposition, moving average, and autoregressive integrated moving average (ARIMA). They demonstrated that incorrect data can be detected automatically and that linear interpolation performs best for filling in blanks. They concluded that data cleaning procedures are essential, and the methods they present can form part of a general data processing methodology for low-cost air quality sensors. They also identified several challenges and opportunities for further research, such as validating data with alternative methods, improving sensor quality, and integrating data from various sources.

1.3. Factors Influencing User Acceptance of Artificial Intelligence

According to Mikalef et al. (2020), a systematic literature study on the factors contributing to users' acceptance of artificial intelligence. They reviewed 36 empirical studies using the 2 Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT) models to examine the effect of variables such as perceived usefulness, perceived ease of use, perceived intelligence, perceived trustworthiness, perceived enjoyment, social influence, facilitating conditions, and behavioral intention towards acceptance of artificial intelligence by users in various application contexts. They found that perceived usefulness and ease of use were the main factors influencing users' acceptance of artificial intelligence in all application contexts. They also found that perceived intelligence and trustworthiness influence user acceptance of artificial intelligence in application contexts involving human-machine interaction or automated decision-making. They recommend several steps to improve the quality of research on user acceptance of artificial intelligence, such as developing comprehensive theoretical models, using appropriate quantitative and qualitative methods, and providing accessible source code and data.

1.4. The Role of Perceived Intelligence in Acceptance of Artificial Intelligence Agents

Kelly et al. (2022) tested the effect of perceived intelligence on users' acceptance of artificial intelligence in the context of artificial intelligence agents providing product recommendations. They used a modified TAM model by adding perceived intelligence as a mediating variable between perceived accuracy and usefulness. They conducted an online survey of 204 respondents who used artificial intelligence agents to search for products on e-commerce platforms. They found that perceived intelligence positively and significantly affects perceived usefulness and behavioral intention. They also found that perceived accuracy positively and significantly affects perceived intelligence. They concluded that perceived intelligence is an essential factor influencing users' acceptance of artificial intelligence in the context of artificial intelligence agents. They recommend several steps to improve the perceived intelligence of artificial intelligence agents, such as providing feedback, explanations, and personalization.

1.5. Air Quality Prediction Based on Machine Learning with Spatial-Temporal Data

Meanwhile, Zhu et al. (2018) developed a machine learning-based air quality prediction model using spatial-temporal data from community sensors in Beijing, China. They used a three-dimensional convolutional neural network (3D-CNN) to extract spatial-temporal features from high-resolution but unstable and incomplete community sensor data. They also used regularization and optimization techniques to improve the performance of the 3D-CNN model. They evaluated the performance of their model using air quality data from official monitoring stations and compared it with multiple linear regression models and two-dimensional convolutional neural network (2D-CNN) models. They show that the 3D-CNN model can provide higher air quality prediction accuracy than other models. They also presented challenges and opportunities for further research, such as using multi-source data, ensemble methods, and model interpretation techniques.

1.6. Air Quality Monitoring System in the context of the Smart City Context

Singh and Ananthanarayanan (2020) developed an air quality monitoring system that measures air pollutants such as SO, NO2, CO, O3, PM 2.5, and PM 10 in real time and uses an optimized algorithm that improves accuracy and reduces system complexity. The deep learning, long short-term memory (LSTM) algorithm will provide a good air quality measurement and effectively control air pollution in smart cities. The author does not explain how the air quality monitoring system might interact with users or authorities related to air pollution. The authors did not evaluate the air quality monitoring system's social, economic, and environmental impacts.

This literature review presents various approaches and previous research relevant to the influence of the perceived accuracy of the AIKU Application on Perceived Usability and Perceived Ease of Use. These studies coherently view the importance of artificial intelligence and Internet of Things (IoT)-based technologies in air quality monitoring. They show how to overcome challenges such as data cleaning and air quality prediction with machine learning algorithms and the factors influencing user acceptance of this technology. Through this literature study, we can understand how the AIKU application can bring significant benefits in detecting air pollution. By understanding the theoretical basis and empirical findings from previous research, this research can continue to explore how the perceived accuracy of the AIKU application influences the use of this application in air quality monitoring as a research novelty, with a direct impact on critical real-world issues related to air pollution and human welfare. This research will make significant contributions to society, including a better understanding of the use of AI technology, improved air quality, increased societal well-being, encouragement for the development of AI technology, a stronger foundation for public policy, and contributions to scientific knowledge.

2. Methods

This study will use a quantitative approach with the online survey method to collect data from prospective respondents using the AIKU application. We have detailed the stages and procedures for data collection, From data collection to hypothesis testing using SmartPLS (PLS-SEM).

2.1. Data collection

A quantitative approach with the online survey method is used to collect data from prospective respondents who use the AIKU application. Google Form was chosen as the questionnaire media because it is easy to use and can be accessed via the internet at any time, with the inclusion and exclusion criteria for respondents who have been set. Inclusion criteria: (1) At least 18 years old, (2) live in Indonesia, (3) have access to the internet and mobile devices, (4) have interest or experience in using the AIKU Application. Exclusion criteria (1) did not meet the inclusion criteria, (2) were not willing to give informed consent, and (3) needed to complete the survey questionnaire wholly and honestly. Questionnaires were distributed for one month, from January 2023 to February 2023, with 317 questionnaires collected data. However, from this data, only 287 questionnaires produced valid data presented in Table 1, according to the criteria to be used as primary data and analyzed using PLS-SEM.

Table 1. Questionnaire result

Category	Information	Amount	Presentation
Gender	Man	53	54.64%
	Woman	44	45.36%
Age	18-27	43	44.33%
	28-38	21	21.65%
	39-49	15	15.46%
	>50	18	18.56%
Customer Tier	Student	47	48.45%
	Lecturer/Teacher	30	30.93%
	Other	20	20.62%

2.2. TAM

This study will use the Technology Acceptance Model (TAM) to measure the influence of factors such as perceived usefulness (PU) and perceived ease of use (PEUO) on attitude (A) and behavior.

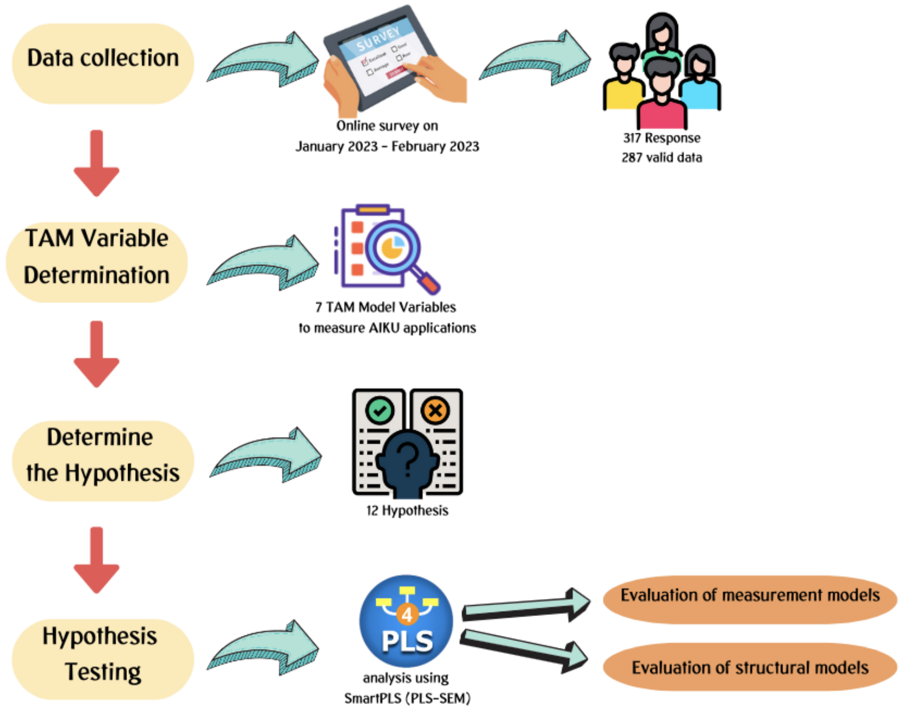

Figure 1. Research Method

Intention (BV) in AIKU applications (Putri et al., 2023). The TAM method is also a model used to explain and predict user behavior towards technology based on two main factors, namely PU and PEOU. According to TAM, these two main factors will influence user attitudes toward technology, which will affect user intentions. to use technology. They ultimately will influence the behavior of the actual use of technology. This study adopts TAM because it is the most widely used and tested information and communication technology model. In addition, this study also adds perceived accuracy (PA), perceived intelligence (PI), and System Quality (SQ) as other external variables that are relevant to the context of artificial intelligence-based air quality monitoring and prediction systems.

- Perceived Accuracy (PA): the user's perception of how accurately AI can detect air quality. PA influences user satisfaction with the AI-enabled air quality detection system.
- Perceived Intelligence (PI): user's perception of how intelligent AI is in air quality detection. PI influences user confidence in the AI-enabled air quality prediction system.
- Perceived Usefulness (PU): user's perception of how useful AI is to help them understand air quality. PU is one of the primary constructs in the TAM model that influences user attitudes and intentions toward technology.
- Perceived Ease of Use (PEOU): the user's perception of how easy it is to use AI to detect air quality. PEOU is one of the primary constructs in the TAM model that influences user attitudes and intentions toward technology.
- Behavioral Intention (BV): the user's intention or desire to use AI to detect air quality regularly or more frequently in the future (Hariguna et al., 2023). BV is the primary dependent variable in the TAM model that reflects users' actual behavior towards technology.
- Attitude (A): Attitude towards using AI is the user's evaluation or assessment of their experience using AI to detect air quality. Attitude is a mediator variable in the TAM model that connects PU and PEOU with BV.
- System Quality (SQ): Technical performance quality from AI in detecting air quality. SQ is one information system success dimension affecting PU and PEOU users (Jimenez et al., 2020).

2.3. Hypotheses

From the several variables that have been determined, 12 hypotheses are determined that these variables will affect PU and PEOU directly or indirectly and will further influence user attitudes, intentions, and behavior towards AIKU applications as artificial intelligence-based monitoring and prediction of air quality.

H1: PA has a positive effect on PU.
H2: PA has a positive effect on PEOU.
H3: PI has a positive effect on PU.
H4: PI has a positive effect on PEOU.
H5: SQ has a positive effect on PU.
H6: SQ has a positive effect on PEOU.
H7: PEUO has a positive effect on PU.
H8: PU has a positive effect on A.
H9: PEUO has a positive effect on A.
H10: PU has a positive effect on BV.
H11: PEUO has a positive effect on BV.
H12: A moderates the influence on BV

2.4. Hypothesis Testing

The hypothesis testing is continued by measuring the five-point Likert Scale shown in Table 2, Samadbeik et al. (2023). The survey instrument includes details about the questions to measure the variables in this model. Thus increasing the clarity and transparency of research instruments. Finally, SmartPLS analysis (PLS-SEM) is used to test the relationship of these variables with the Research Framework in Figure 2. With the instruments developed and data collection procedures described, this research will enable valid and high-quality data collection and in-depth analysis regarding user acceptance and behavior towards the AIKU application.

Table 2. The research instrument was a five-point Likert Scale question

Variables		Statement
Perceived Accuracy (PA)	PA1	I feel that the AIKU App can accurately detect air quality.
	PA2	I feel the AIKU App provides correct information about air quality.
	PA3	I feel that the AIKU App is consistent in detecting air quality.
	PA4	I feel that the AIKU Application can detect air quality in various locations and conditions.
Perceived Intelligence (PI)	PI1	I feel that the AIKU application has a high ability to detect air quality.
	PI2	I feel that the AIKU App can adapt to changes in air quality.
	PI3	The AIKU App can learn from previous experiences in detecting air quality.
	PI4	I feel that the AIKU App can provide useful suggestions or recommendations based on the results of air quality detection.
Perceived Usefulness (PU)	PU1	I feel that the AIKU Application is useful to help determine air quality.
	PU2	I feel that the AIKU App increases effectiveness in making decisions regarding air quality.

	PU3	The AIKU App makes it easy to access information about air quality.
	PU4	I feel the AIKU App improves health and well-being by providing information about air quality.
Perceived Ease of Use (PEOU)	PEOU1	I find the AIKU App easy to use for detecting air quality.
	PEOU2	The AIKU App requires little effort to detect air quality.
	PEOU3	I feel the AIKU App has a user-friendly interface for detecting air quality.
	PEOU4	The AIKU App doesn't need much help or instructions to detect air quality.
Attitude (A)	A1	I am positive about using the AIKU App to detect air quality.
	A2	I enjoy using the AIKU App to detect air quality.
	A3	I am satisfied with my experience using the AIKU Application to detect air quality.
	A4	I recommend using the AIKU App to detect air quality in people.
Behavioral Intention (BI)	BI1	I intend to use the AIKU App to detect air quality regularly.
	BI2	I intend to use the AIKU App to detect air quality more frequently.
	BI3	I intend to continue using the AIKU App to detect air quality for as long as I need it.
System Quality (SQ)	SQ1	I feel that the AIKU Application has good speed in detecting air quality.
	SQ2	I feel that the AIKU Application has good reliability in detecting air quality.
	SQ3	I feel that the AIKU Application has good flexibility in detecting air quality.
	SQ4	I feel that the AIKU application has complete functions in detecting air quality.

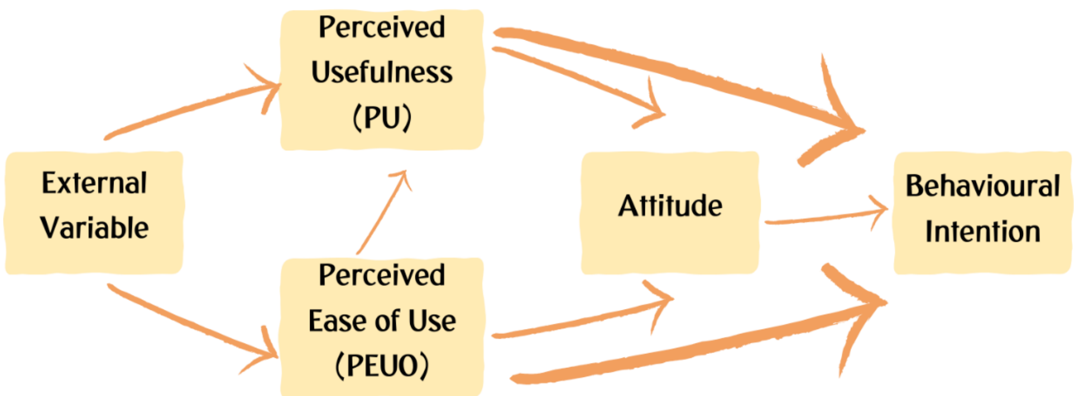

Figure 2. The AIKU Research Framework Uses the TAM Model

3. Results and Discussion

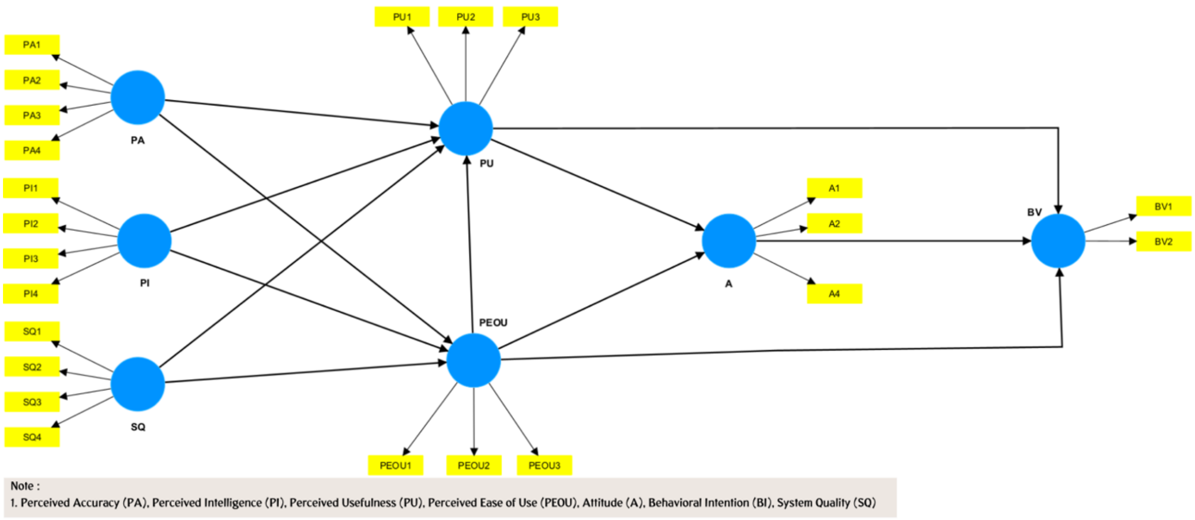

Figure 3 SmartPLS Model Structure

Developing research instruments involves several important steps in testing the hypothesis using SmartPLS. First, the data to be used needs to be processed to eliminate invalid values where the Outer Loading value must be above 0.7 (> 0.7) because this value shows that an indicator (question in the questionnaire) has a strong relationship with the construct being measured. After that, a structural model was created in Figure 3. Then, the existing variables were connected for analysis. In this research, three evaluations were used to develop research instruments, namely evaluation with model measurement analysis and structural measurement analysis.

3.1. Model Measurement Analysis

In conducting model measurement analysis, several aspects need to be considered.

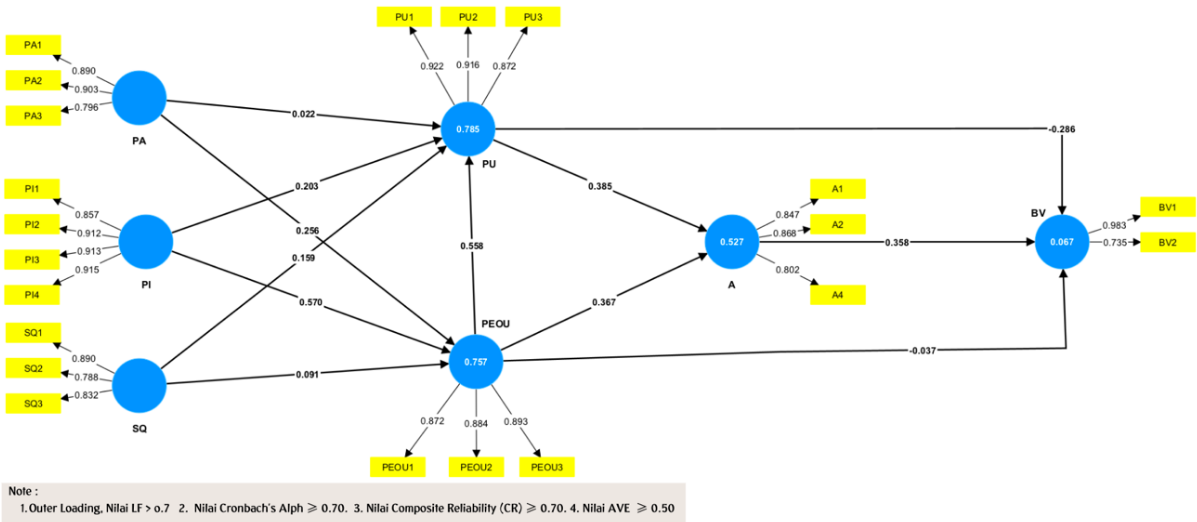

Figure 4. Final Result Model

3.1.1. Validation of the outer loading

Table 3. Outer loading value

Variable	Outer loadings	Variable	Outer loadings
A1 <- A	0.847	PI1 <- PI	0.857
A2 <- A	0.868	PI2 <- PI	0.912
A4 <- A	0.802	PI3 <- PI	0.913
BV1 <- BV	0.983	PI4 <- PI	0.915
BV2 <- BV	0.735	PU1 <- PU	0.922
PA1 <- PA	0.887	PU2 <- PU	0.916
PA2 <- PA	0.899	PU3 <- PU	0.872
PA3 <- PA	0.797	SQ1 <- SQ	0.889
PA4 <- PA	-0.236	SQ2 <- SQ	0.79
PEOU1 <- PEOU	0.872	SQ3 <- SQ	0.831
PEOU2 <- PEOU	0.884	SQ4 <- SQ	0.043
PEOU3 <- PEOU	0.893		

The outer loading value indicates the convergent validity of the indicator, namely how well the indicator reflects the same latent variable. The outer loading value provisions are considered valid/ideal if the resulting value is greater than or equal to 0.7 (≥ 0.7); the indicator must be removed if it is less than these conditions. In Figure 4, the invalid indicator values have been removed so that the model can be used to measure variables. From the data generated in Table 3, there are 21 valid/accepted variable values because the resulting values exceed >0.7, and there are two invalid/rejected variable values. In conducting model measurement analysis, several aspects need to be considered.

3.1.2. Reablititas CR (Composite reliability) & AVE (Average variance extracted)

Table 4. Instruments reliability

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	Result
A	0.79	0.79	0.878	0.705	Accepted
BV	0.749	1.838	0.857	0.753	Accepted
PA	0.83	0.845	0.898	0.746	Accepted
PEOU	0.859	0.859	0.914	0.78	Accepted
PI	0.921	0.927	0.944	0.81	Accepted
PU	0.888	0.89	0.93	0.817	Accepted
SQ	0.789	0.818	0.875	0.701	Accepted

Table 4 presents the reliability analysis results on the seven variables measured using smartPLS with data collected from the previous questionnaire. The research concludes that the variable's reliability level is "accepted" based on the CR and AVE values.

- The Cronbach's Alpha value provision is preferably a deal greater than or equal to 0.7 (≥ 0.70). Internal reliability is considered low or unacceptable if Cronbach's Alpha value is less than <0.6. All variables' internal reliability/consistency is acceptable, while the PEUO and SQ variables are rejected.
- All variables' Composite Reliability (CR) value is≥ 0.70, indicating that the variable reliability level is accepted. This is based on the same CR provisions as Cronbach's Alpha.
- The AVE value shows a value of ≥ 0.50, so it meets the requirements of good convergent validity. Overall, the variables have an AVE value ≥ 0.50; therefore, the concurrent validity of the variable is accepted.

3.1.3. HTMT (Heterotrait-Monotrait Ratio)

HTMT was used to evaluate discriminant validity between constructs. HTMT has an advantage over Fornell-Locker Criterion & Cross Loading because it has a better level of accuracy. This is important to ensure that the constructs being measured have a weak relationship with one another. The provisions for using HTMT are that if the HTMT value between the two constructs is less than 0.9 (<0.9) variable, then it can be said that the discriminant validity between the constructs is sufficiently fulfilled. If the HTMT value exceeds 0.9 (> 0.9), it indicates a multicollinearity problem that can affect the interpretation of the analysis results. In Table 5, the HTMT values between the constructs BV -> A, PA -> BC, and SQ -> PU are sufficiently met, while the other constructs are not met. Therefore, special handling is needed to reduce multicollinearity and ensure the validity of better analysis results.

Table 5. HTMT (Heterotrait-Monotrait Ratio) values

	A	BV	PA	PEOU	PI	PU	SQ
A							
BV	**0.192**						
PA	0.962	**0.057**					
PEOU	0.85	0.173	0.936				
PI	0.913	0.104	0.935	0.955			
PU	0.838	0.144	0.866	0.989	0.906		
SQ	0.877	0.127	0.93	0.872	0.913	**0.88**	

3.2. Analysis of Reflective Structural Measurements

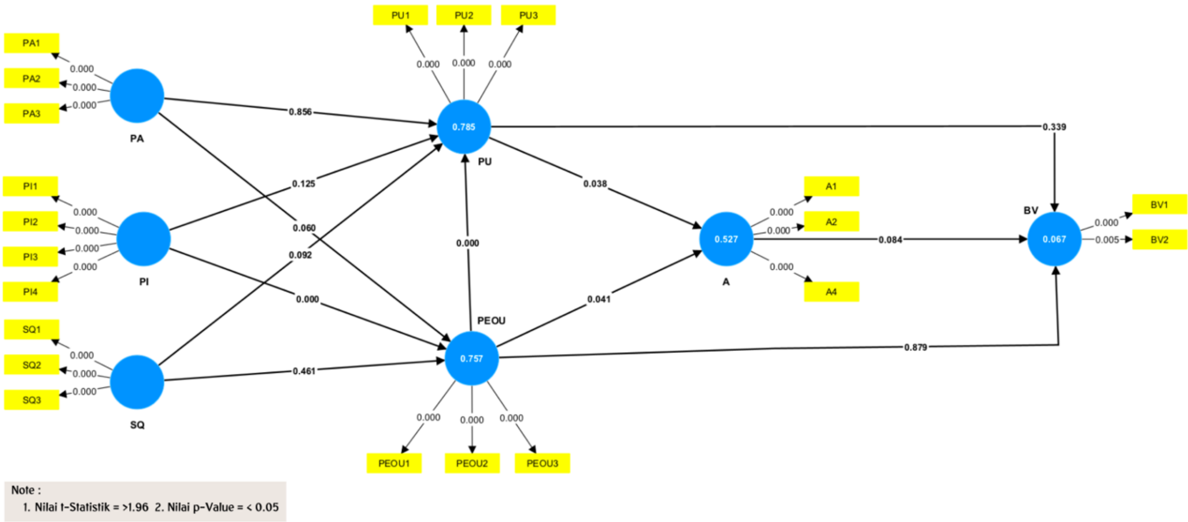

Figure 5. Bootstrapping calculation results

Analysis of Reflective Structural Measurements was carried out to test the hypothesis regarding the statistical validity test of the relationship between latent variables in the structural model of the study. Figure 5 shows the value Bootstrapping calculated to display the t-statistics value and p-value.

Table 5. Hypothesis test results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Influence	Results
A -> BV	0.358	0.338	0.207	1.73	0.084	Not Significant	Rejected
PA -> PEOU	0.256	0.245	0.137	1.878	0.06	Not Significant	Rejected
PA -> PU	0.165	0.154	0.138	1.199	0.231	Not Significant	Rejected
PEOU -> A	0.581	0.577	0.103	5.65	0	Significant	Accepted
PEOU -> BV	0.012	0.025	0.153	0.079	0.937	Not Significant	Rejected
PEOU -> PU	0.558	0.557	0.152	3.672	0	Significant	Accepted
PI -> PEOU	0.57	0.567	0.133	4.275	0	Significant	Accepted
PI -> PU	0.521	0.514	0.163	3.192	0.001	Significant	Accepted
PU -> A	0.385	0.383	0.185	2.077	0.038	Significant	Accepted
PU -> BV	-0.148	-0.087	0.267	0.554	0.58	Not Significant	Rejected
SQ -> PEOU	0.091	0.103	0.124	0.738	0.461	Not Significant	Rejected
SQ -> PU	0.21	0.22	0.116	1.806	0.071	Not Significant	Rejected

The results in Table 5 show that not all the hypotheses proposed are accepted; there are five hypotheses accepted and seven hypotheses rejected; this is because the original sample values (Path Coefficients), t-statistics, and p-values do not comply with the existing provisions where they should be the original sample value (Path Coefficients) is close to +1, the t-statistic value is more significant than 1.96, and the p-value is less than 0.05.

H1: PA has a positive effect on PU.

Testing the PA hypothesis has no significant effect on PU, with a t-statistic value = 1.199 > 1.96, p-value = 0.231 <0.05, and Original sample (Path Coefficients) 0.165, meaning H1 is declared rejected.

H2: PA has a positive effect on PEOU.

Testing the PA hypothesis has no significant effect on PEUO, with a t-statistic value = 1.878 > 1.96, p-value = 0.06 <0.05, and the Original sample (Path Coefficients) 0.256, meaning H2 is declared rejected.

H3: PI has a positive effect on PU.

Testing the PA hypothesis significantly affects PU, with a t-statistic value = 3.192 > 1.96, p-value = 0.001 <0.05, and Original sample (Path Coefficients) 0.521, meaning that H3 is declared accepted.

H4: PI has a positive effect on PEOU.

Testing the PA hypothesis significantly affects PEUO, with a t-statistic value = 4.275 > 1.96, p-value = 0 <0.05, and Original sample (Path Coefficients) 0.57, meaning that H3 is declared accepted.

H5: SQ has a positive effect on PU.

Testing the hypothesis, PA has no significant effect on PU, with a t-statistic value = 1.806 > 1.96, p-value = 0.071 <0.05, and Original sample (Path Coefficients) 0.21, meaning H5 is declared rejected.

H6: SQ has a positive effect on PEOU.

In testing the hypothesis, PA has no significant effect on PEUO, with a t-statistic value = 0.738 > 1.96, p-value = 0.461 <0.05, and the Original sample (Path Coefficients) 0.091, meaning H6 is rejected.

H7: PEUO has a positive effect on PU.

Testing the PEUO hypothesis significantly affects PU, with a t-statistic value = 3.672 > 1.96, p-Value = 0 <0.05, and Original sample (Path Coefficients) 0.558, meaning that H7 is declared accepted.

H8: PU has a positive effect on A.

Testing the PU hypothesis significantly influences A, with a t-statistic value = 2.077 > 1.96, p-value = 0.038 <0.05, and Original sample (Path Coefficients) 0.385, meaning that H8 is declared accepted.

H9: PEUO has a positive effect on A.

Testing the PEUO hypothesis significantly influences A, with a t-statistic = 5.65 > 1.96, p-value = 0 <0.05, and Original sample (Path Coefficients) 0.581, meaning that H9 is declared accepted.

H10: PU has a positive effect on BV.

Testing the PU hypothesis has no significant effect on BV, with a t-statistic value = 0.554 > 1.96, p-value = 0.58 <0.05, and the Original sample (Path Coefficients) -0.148, meaning that H6 is rejected.

H11: PEUO has a positive effect on BV.

In testing the PEUO hypothesis, it has no significant effect on BV, with a t-statistic value = 0.079 > 1.96, p-value = 0.937 <0.05, and the Original sample (Path Coefficients) 0.012, meaning H11 is declared rejected.

H12: A moderates the influence on BV.

Testing hypothesis A has no significant effect on BV, with a t-statistic value = 1.73 > 1.96, p-value = 0.084 <0.05, and Original sample (Path Coefficients) 0.358, meaning H12 is declared rejected.

All the results show that H3, H7: PI, and PEUO positively and significantly affect PU. H4: PI has a positive and significant effect on PEOU. H8, H9: PU, PEOU positively and significantly impact A. Meanwhile, the five hypotheses were rejected. H1, H5: PA, and SQ did not significantly affect PU. H2, H6: PA, and SQ do not significantly affect PEOU. H10, H11, H11: PU, PEOU, A do not significantly affect Behavioral Intention. Overall, the research results show no significant evidence to support the statements H1 and H2 in testing the hypothesis. This means that, in the context of this research, the PA (Perceived Accuracy) variable does not have a significant influence on PU (Perceived Usability) and PEOU (Perceived Ease of Use). These findings illustrate that users' perceptions of application accuracy do not directly influence the perceived ease of use of the application and users' intention to use it. Nonetheless, other positive findings from this research show that other factors such as PI (Perceived Importance) and PEUO (Perceived Ease of Use) have a significant influence on PU (Perceived Usability) and users' intention to use the application, which has essential safeguards in the development of AI-based air quality applications.

4. Conclusion

The conclusion of this study brings several relevant and significant findings regarding the acceptance and use of the AIKU Application in the context of air quality monitoring. Although several findings support the research hypothesis, several challenges and limitations must be considered. This study found that the perceived accuracy (PA) of AIKU applications did not directly impact Perceived Usability and Perceived Ease of Use. However, PA still indirectly influences users' intentions and attitudes towards the application. Perceived Intelligence and Ease of Use mediate the relationship between PA and Perceived Usability, and Perceived Ease of Use influences User Attitude. The main challenge faced in this research is that perceived accuracy does not directly influence application usage. This suggests that users may not consider the level of accuracy to be a key factor in assessing app usability. Therefore, developers of similar applications should pursue improving accuracy while ensuring ease of use as a top priority. In addition, the limitations of the data and samples used in this study also pose a challenge in generalizing the study's results to a broader population.

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This research attempts to test user acceptance of an AI-based system that can provide accurate information about air quality. This research is expected to develop theory and practice in technology and environmental management. This research will also benefit the government and society by supporting systems that can help improve public health and welfare. The author wants to thank all parties who have assisted and supported this research, especially the supervising lecturers who have provided valuable guidance and advice. Remember to thank the respondents willing to take the time and energy to complete the questionnaire. Hopefully, this research can be helpful for the development of science and the benefit of the people.

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