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User Satisfaction of Artificial Intelligence Air Quality Detection: UTAUT2 Approach

Untung Rahardja[*1], Putri Marewa Oganda[2], Sri Watini[3], Nesti Anggraini Santoso[4]
[1,4] Department of Digital Business, Faculty of Economics & Business,
University of Raharja, Indonesia
[2] Department of Computer Science, Faculty of Science Education,
Georgetown University, United States
[3] Department of Early childhood education, Faculty of Science Education,
Panca Sakti University, Indonesia
E-mail: [*1]**untung@raharja.info**, [2]putrimarewaoganda@adi-journal.org,
[3]sriwatini@panca.sakti.ac.id, [4]nesti@raharja.info

Abstract

The application of Artificial Intelligence (AI) in air quality detection represents a significant technological advancement with potential global and local implications. This technology not only aids the public in monitoring environmental conditions but also offers valuable insights into pollution levels, health impacts, and actionable recommendations that are critical for public health management. Given the universal challenge of air pollution, particularly in urban areas, this study aims to provide a comprehensive understanding of how AI-based air quality detection systems can be effectively utilized across different geographic and socio-economic contexts. However, the usage of this application is still constrained by various factors that influence user satisfaction. This study aims to examine the impact of elements within the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model on user satisfaction with AI-based air quality detection applications. The UTAUT2 model comprises 9 constructs. This research employs an online survey method with a sample of 150 respondents who have used AI-based air quality detection applications. Data were analyzed using the PLS-SEM (Partial Least Square Structural Equation Modeling) technique using SmartPLS4. The research findings indicate that only Performance Expectancy and Behavioral Intention significantly influence usage intention and behavior of the application. These findings highlight the critical role of user intention and performance expectations in determining usage behavior and user satisfaction. The practical implications and theoretical of this study, including recommendations for application developers and future researchers, are further discussed in this research.

Keywords *— Air Quality Detection Application, Artificial Intelligence, User Satisfaction, Model Utaut2*

1. INTRODUCTION

Artificial intelligence (AI) technology has profoundly transformed various aspects of modern life, including environmental monitoring and management. Air quality issues represent a critical global challenge, with significant health and environmental implications that transcend national borders [1]. While Indonesia, particularly its urban centers, faces acute air quality problems, similar challenges are prevalent worldwide, making the development and adoption of AI-based solutions universally relevant [2]. This study investigates the adoption of

AI-powered air quality detection systems, aiming to contribute to the global discourse on environmental technology while providing localized insights that can inform both domestic and international applications.. AIKU (Artificial Intelligence Kualitas Udara) is a revolutionary system that uses artificial intelligence to identify and monitor air quality in real time [3]. This application is designed to provide accurate and up-to-date information to the public, allowing them to take preventative actions to reduce the harmful health impacts of air pollution [4-5]. Previous research has explored the use of AI in various environmental monitoring applications across different contexts. However, a notable gap remains in understanding the user satisfaction and acceptance of AI-based air quality monitoring systems, particularly within developing countries like Indonesia.

This study seeks to bridge this gap by not only focusing on the Indonesian context but also drawing broader implications that can inform the deployment of similar technologies in diverse global settings, thereby contributing to the generalizability of AI adoption models [6]. Studies such as those by [7] have primarily focused on technical performance and data accuracy of air quality monitoring systems, but have not sufficiently addressed user experience and satisfaction. This gap highlights the need for a more comprehensive understanding of the factors that influence user satisfaction with such technologies, especially in developing countries like Indonesia where environmental and technological contexts may differ significantly from those in more developed regions.

The acceptance and adoption of new technologies like AIKU heavily depend on user satisfaction. This satisfaction is a key indicator in determining the success and sustainability of such technologies. To address the identified gap, a comprehensive theoretical approach is necessary. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model offers an effective framework for analyzing technology acceptance [8]. This model encompasses various factors, such as Performance Expectancy (PEXP), Effort Expectancy (EEX), Social Influence (SOI), Facilitating Conditions (FC), Hedonic Motivation (HEM), Price Value (PRV), And Habit (HB), all of which can impact User Satisfaction (USS) and technology usage. This study aims to identify and analyze the factors within the UTAUT2 model that affect user satisfaction with the AIKU application in Indonesia. By understanding these factors, application developers can enhance and improve the features and functions of AIKU to better meet user needs and expectations [9]. Additionally, the results of this research are expected to assist in increasing the broader adoption of AI-based air quality monitoring technology among the Indonesian public. Consequently, this study not only contributes to the academic literature but also provides practical recommendations for technology developers and policymakers in their efforts to improve air quality in Indonesia. The structure of this study is as follows: Chapter 2 provides a literature review on air quality, AI, and the UTAUT2 model, and presents the research methodology, including research design, measurement instruments, sampling techniques, and data analysis. Chapter 3 shows the results of the data analysis and discussion of the findings. Chapter 4 concludes this study and future work

2. RESEARCH METHOD

2.1. Literature Review

Research on air quality and the adoption of technology using the UTAUT2 model has yielded various vital findings relevant to the topic "User Satisfaction of Artificial Intelligence Air Quality Detection: UTAUT2 Approach." [10] in his study on Air-MIT, an IoT-based air quality monitoring device, found that this system can detect harmful gases such as CO_2, CO, CH_4, and NH_4 in real time. It also triggers alarms and activates ventilation automatically to reduce the concentration of dangerous gases. However, this study focuses on indoor monitoring and does not evaluate user acceptance or satisfaction with this technology. [11] extended the UTAUT2 model by including proactive personality variables to study the adoption of mobile banking. The results showed that proactive personality significantly influences users' intentions to adopt technology through UTAUT2 perceptions [12]. This highlights the relevance of personality in influencing technology adoption, which can also be applied to AI-based air quality monitoring. However, this study focuses on mobile banking in developing countries and may not be fully generalizable to other technologies. [13] proposed a method for air quality prediction using deep learning (3D-CNN) based on images. This approach allows for more transparent and cost-effective predictions of air quality features. Nevertheless, the study primarily addresses technical aspects and less on user adoption and satisfaction. [14]utilized machine learning algorithms to predict air quality with long- term data. This model helps understand hidden patterns in air quality data. However, the study does not consider social and psychological factors affecting user acceptance and satisfaction with air quality monitoring technology. [15] conducted a comparative analysis of air quality prediction using machine learning. This study is relevant for understanding how the public can accept and use AI-based predictive models. Unfortunately, it emphasizes technical analysis more and less explores how users receive this technology and how user satisfaction is measured.

This research presents a significant opportunity to address the shortcomings of previous studies by focusing on the Indonesian context through the AIKU (Artificial Intelligence Kualitas Udara) application. The development of AIKU can explore user acceptance and satisfaction with AI-based air quality monitoring systems, an aspect that has yet to be widely studied. By considering social and psychological factors influencing technology acceptance, this research can provide a more comprehensive understanding of how this technology can be effectively adopted and used in Indonesia. Additionally, AIKU can be developed for indoor and outdoor air quality monitoring, offering a more holistic and locally relevant solution. This study can also identify strategies to increase public awareness and acceptance of air quality monitoring technology and evaluate its impact on health and the environment.

2.2. Method

This study employs a quantitative approach to measure the impact of variables within the UTAUT2 model on user satisfaction with AI-based air quality detection applications [16]. The UTAUT2 model was selected because of its proven effectiveness in assessing technology acceptance and usage across various contexts, including emerging technologies and AI-based applications. UTAUT2 provides a comprehensive framework by incorporating factors such as

Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, and Behavioral Intention, all of which are considered relevant in the context of AI-based air quality detection applications [17].

The choice of UTAUT2 over other models, such as the Technology Acceptance Model (TAM) or Diffusion of Innovation (DOI), is justified by its ability to capture a broader range of psychological and social factors influencing technology acceptance. UTAUT2's inclusion of variables like Hedonic Motivation and Habit offers deeper insights into the factors that influence user satisfaction, particularly in the adoption of relatively new technologies such as AI-based air quality detection applications in Indonesia. Furthermore, UTAUT2 allows for a more comprehensive analysis of user intentions and behavior, which is crucial in understanding the dynamics of technology adoption among users in Indonesia.

2.2.1. Data Collection

This study employed a 24-item instrument to measure the 8 constructs of UTAUT2 which is shown in figure 1, using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). This scale was selected to minimize cognitive bias and respondent confusion. PLS-SEM (Partial Least Squares Structural Equation Modeling) was used to analyze the data, as it allows for simultaneous testing of relationships between observed and latent variables, combining multiple regression analysis with factor analysis and providing overall fit statistics [18]. PLS-SEM also accounts for measurement errors in observed variables, offering a more accurate understanding of factors influencing user satisfaction with AI-based air quality detection technology.

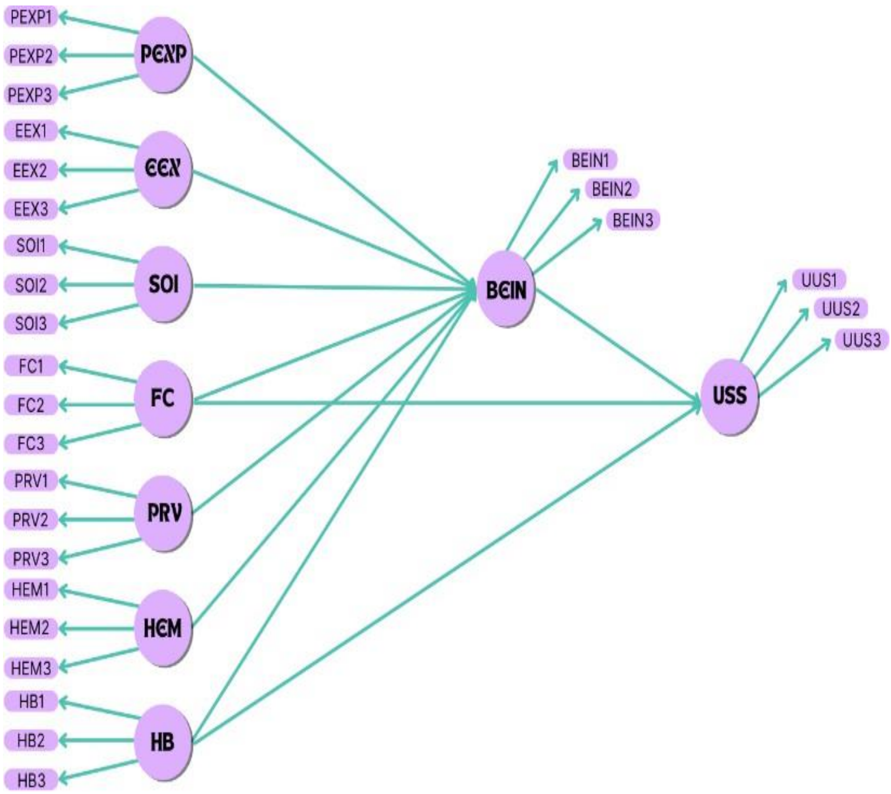

Figure 1. Research Instrument

This research explores the key aspects influencing the usage and user satisfaction of AI- based air quality detection applications [9]. **Performance Expectancy (PEXP)** describes the extent to which users believe that the application helps them detect air quality. **Effort Expectancy (EEX)** portrays the ease of use perceived by users regarding the application. **Social Influence (SOI)** refers to users' perception that important people in their lives support using the application. **Facilitating Conditions (FC)** describe users' belief that the existing infrastructure supports the application's usage. **Price Value (PRV)** reflects users' belief that the application's benefits outweigh the costs, whether in terms of time, money, or other resources. **Hedonic Motivation (HEM)** refers to the extent to which users find using the application enjoyable. **Habit (HB)** explains the extent to which the application usage becomes part of users' daily routines. **Behavioral Intention (BEIN)** depicts users' Intention to continue using the application in the future. And finally, **User Satisfaction (USS)** represents the satisfaction users have with the application, which is the ultimate goal of this research.

The analysis method for this study utilizes SmartPLS4 with the UTAUT2 approach [19]. Firstly, the collected and organized survey data will be imported into the SmartPLS4 software. Before testing the research hypotheses, the measurement model is assessed to ensure reliability and validity. This involves examining the Average Variance Extracted (AVE) values for convergent validity and ensuring that the square root of the AVE for each construct is greater than the correlation between that construct and other constructs for discriminant validity. The Cronbach's Alpha and Composite Reliability (CR) values are also checked to assess reliability, with values above 0.7 considered acceptable [20]. After validating the measurement model, the structural model is tested. This involves assessing the paths and testing the direct, indirect, and total effects between constructs. Additionally, the R-square values are examined to determine how much variance in the dependent constructs can be explained by the model [21]. To examine the significance of relationships in the model, the bootstrap technique is employed within SmartPLS. This technique generates confidence intervals for path estimates, which can be used to determine the significance of the relationships between constructs. Once all the analyses are completed, the results are interpreted within theory and previous research context. Any significant or non-significant relationships between constructs should be explained, and the implications of these findings for research and practice should be discussed. The entire process should be conducted carefully and systematically to ensure high-quality research.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

In the context of this research, 250 respondents were selected based on relevant criteria, including an age range of 15 to over 35 years and a requirement of having at least one experience using the AI-based air quality detection application. Out of the total respondents, 150 respondents, or 60%, met the criteria, and their questionnaire responses were utilized in this study. Meanwhile, 100 respondents, or 40%, were eliminated due to needing to meet the specified criteria in this research.

3.2. Model Quality

After the data collection stage, the next step is to ensure the quality of the model used in the analysis. This is crucial to guarantee that the results obtained from the model are valid and reliable. One way to assess the quality of the model is by evaluating the Outer Loading values. The Outer Loading Value is an indicator of how well the indicators reflect the construct being measured. The results of the PLS Algorithm using SmartPLS 4 provide the necessary metrics for this evaluation.

Figure 2. Result Data Collection

Table 1. and Figure 1. presents the Outer Loading Value results used to assess the convergent validity of the constructs tested. Outer Loading values greater than 0.7 indicate that the indicators have a strong relationship with their constructs, while values below 0.7 need to be reviewed and possibly improved or removed from the model.

Table 1. Outer Loading Value Results

	BEIN	EEX	FC	HB	HEM	PEXP	PRV	SOI	USS
BEIN1	**0.042**								
BEIN2	0.891								
BEIN3	0.909								
EEX1		0.819							
EEX2		0.843							
EEX3		0.779							
FC1			0.716						
FC2			0.617						
FC3			0.675						
HB1				0.92					
HB2				0.33					
HB3				0.716					
HEM1					0.933				
HEM2					0.787				
HEM3					0.644				
PEXP1						0.883			
PEXP2						0.905			
PEXP3						0.871			
PRV1							0.704		
PRV2							0.864		

From Table 1. it can be seen that most of the indicators have quite high Outer Loading values, this shows that these indicators are valid in measuring the construct in question. However, there are several indicators such as BEIN1 and H2 which have values below the recommended threshold, even in some cases negative, which indicates there is a problem with the validity of these indicators. Therefore, the next step is to carry out further evaluation of the indicators by considering eliminating negative indicators in order to improve the overall quality of the model

3.3. Measurement Model

In the initial phase, the measurement model testing was conducted to evaluate reliability, convergent validity, and discriminant validity [25]. The PLS algorithm was implemented, and outer weights were calculated for each indicator in the 9 UTAUT2 variables. The evaluation of construct reliability and validity is crucial in ensuring that the measurement model is both reliable and valid. The table below presents the results of the reliability and validity tests, including Cronbach's Alpha, Composite Reliability (rho_a and rho_c), and Average Variance Extracted (AVE) for each construct [22]. These metrics help to assess the internal consistency and convergent validity of the constructs. Generally, Cronbach's Alpha values above 0.7, Composite Reliability values above 0.7, and AVE values above 0.5 are considered acceptable indicators of reliability and validity [23].

Table 2. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BEIN	0.451	0.768	0.711	0.541
EEX	**0.747**	0.759	0.855	0.662
FC	0.428	-0.544	0.354	0.294
HB	0.573	0.75	0.716	0.489
HEM	**0.785**	-1.039	0.448	0.316
PEXP	**0.864**	0.868	0.917	0.786
PRV	0.688	0.328	0.718	0.506
SOI	0.675	0.766	0.757	0.523
USS	**0.746**	1.067	0.836	0.635

These findings on Table 2. confirm the reliability and construct validity of the measurement model. Most constructs exhibit satisfactory values, indicating that the items used in the study are consistent and valid in measuring the intended constructs. However, some constructs with lower values may need further investigation and refinement.Research by [26] revealed that the Heterotrait-Monotrait (HTMT) correlation ratio is more responsive than the Fornell-Larcker criteria. Following their recommendation, this study calculated the HTMT ratio for the correlations between each construct and all inter-construct correlations. The authors also conducted a bootstrap procedure with 1000 samples and computed confidence intervals.

Discriminant validity indicates how much a construct can be distinguished from other constructs. In this study, discriminant validity was evaluated using the Fornell-Larcker criterion and the HTMT criterion.

Table 3. Discriminant Validity - Heterotrait-Monotrait Ratio (HTMT).

	BEIN	**EEX**	**FC**	**HB**	**HEM**	**PEXP**	**PRV**	**SOI**	**USS**
BEIN									
EEX	0.884								
FC	1.03	0.259							
HB	1.74	0.286	0.346						
HEM	1.498	0.12	0.314	0.748					

	BEIN	EEX	FC	HB	HEM	PEXP	PRV	SOI	USS
PEXP	1.24	0.379	0.125	0.07	0.202				
PRV	1.255	0.192	0.639	0.843	0.693	0.121			
SOI	0.633	1.001	0.382	0.257	0.2	0.228	0.119		
USS	1.631	0.274	0.386	0.119	0.162	0.623	0.136	0.127	

Regarding the second criterion, this study utilized the heterotrait-monotrait (HTMT) ratio [27]. Considering that the values of reflective variables fall below the most conservative threshold, there is strong evidence that the internal validity of the measurement model appears to be sufficiently adequate. Each item's high and significant loadings on their respective constructs also indicate convergence validity. Overall, assessing the scale's psychometric characteristics suggests unidimensionality and conceptual consistency.

3.4. Struktural Model

The PLS algorithm calculates the coefficient of determination (R2), representing the proportion of the dependent variable explained by the independent variables. In the context of this study, the R2 for BEIN is recorded as 0.394. Similarly, the R2 for USS is 0.395, also considered moderate. Significance is determined by conducting a bootstrap process with 5000 samples, and no significant changes were observed.

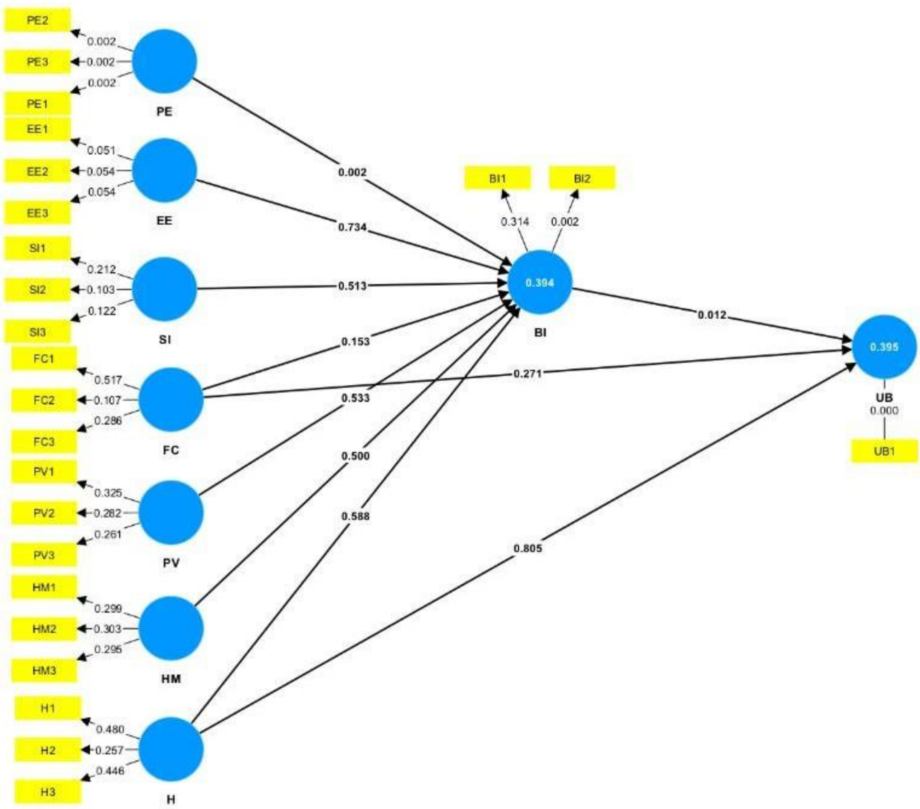

Figure 3. PLS Bootstrapping

As shown in Figure 3, this analysis was conducted using the bootstrap method in SmartPLS Ver 4.0. In this stage, three types of testing were performed: the Coefficient of Determination (R2) test, the Path Coefficient (β) test, and the t-test. The first step was to test the Coefficient of Determination (R2) values. The Coefficient of Determination measures how much a specific independent latent variable influences the latent dependent variable. Based on previous research conducted by Raihan & Rachmawati (2019), R2values of 0.67 (strong), 0.33 (moderate), and 0.19 (weak) were considered.

Table 4. Results of R Square Value

Variabel	**R-square**
BEIN	0.394
User Satisfaction	0.395

The constructs that show significant relationships will provide additional insights into the interconnections between BEIN, users' perceptions of the application, and how it impacts User Satisfaction. Within this study's scope, the structural model findings demonstrate how the UTAUT2 aspects influence users' intentions and satisfaction using AI-based air quality detection applications. This analysis is crucial in understanding the various factors that drive users to adopt such applications and how their usage impacts their level of satisfaction.

Table 5. Significance of Model Paths

	Path coefficient	t-values	P values	Conclusion
BEIN -> USS	**0.525**	**2.507**	0.012	**Signifikan**
EEX -> BEIN	-0.05	0.34	0.734	Not Signifikan
FC -> BEIN	0.281	1.43	0.153	Not Signifikan
FC -> USS	0.226	1.1	0.271	Not Signifikan
HB -> BEIN	0.088	0.541	0.588	Not Signifikan
HB -> USS	-0.037	0.247	0.805	Not Signifikan
HEM -> BEIN	-0.15	0.675	0.5	Not Signifikan
PEXP -> BEIN	**0.383**	**3.112**	0.002	**Signifikan**
PRV -> BEINI	-0.131	0.624	0.533	Not Signifikan
SOI -> BEIN	-0.108	0.655	0.513	Not Signifikan

H1: Behavioral Intention (BEIN) significantly influences Satisfaction (USS) in the adaptation of AIKU usage. After conducting the Path coefficient test, the obtained result is 0.525, indicating that the hypothesis (BEIN → USS) is accepted. Hypothesis testing was also performed using the t-Test with bootstrapping; the result is 2.507, more significant than 1.96. According to Ghozali (2008), the hypothesis is considered significant if the T-statistic is less than 1.96. Therefore, based on the results of both tests, it can be concluded that the BEINvariable significantly influences the USS variable.

H2: Effort Expectancy (EEX) influences BEIN in adapting AIKU usage. The result is consistent with the strong coefficient of determination ($R2 = 0.69$) between EEX and BEIN. However, after conducting the Path coefficient test, the result (-0.05) indicates that Hypothesis H2 (EEX → BEIN) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 0.36, less than 1.96. According to Ghozali (2008), the hypothesis is considered insignificant if the T-statistic is less than 1.96. Based on the results of both tests, it can be concluded that the EEX variable does not significantly influence the BEIN variable.

H3: Facilitating Conditions (FC) influence BEIN in adapting to AIKU. The results are consistent with the FC to BEIN path, which has a strong coefficient of determination ($R2 = 0.69$). However, after conducting the Path coefficient test, the result (0.281) indicates that Hypothesis H3 (FC → BEIN) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 1.43, less than 1.96. According to Ghozali (2008), the hypothesis is considered insignificant if the T-statistic is less than 1.96. Based on the results of both tests, it can be concluded that the FC variable does not significantly influence the BEIN variable.

H4: FC influence USS in adapting to AIKU. The results are consistent with the FC to USS path, which has a strong coefficient of determination ($R2 = 0.69$). However, after conducting the Path coefficient test, the result (0.226) indicates that Hypothesis H4 (FC → USS) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 1.43, less than 1.96. According to Ghozali (2008), the hypothesis is considered insignificant if the T-statistic is less than 1.96. Based on the results of both tests, it can be concluded that the FC variable does not significantly influence the USS variable.

H5: Habit (HB) influences BEIN in adapting to AIKU. The results are consistent with the FC to USS path, which has a strong coefficient of determination ($R2 = 0.69$). However, after conducting the Path coefficient test, the result (0.088) indicates that Hypothesis H5 (FC → BEIN) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 0.541, less than 1.96. According to Ghozali (2008), the hypothesis is considered insignificant if the T-statistic is less than 1.96. Based on the results of both tests, it can be concluded that the HB variable does not significantly influence the BEIN variable.

H6: HB influences USS in adapting to the use of AIKU. The results are consistent with the FC to USS path, which has a strong coefficient of determination ($R2 = 0.69$). However, after conducting the Path coefficient test, the result (0.037) indicates that Hypothesis H6 (HB → USS) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 0.247, less than 1.96. According to Ghozali (2008), the hypothesis is considered insignificant if the T-statistic is less than 1.96. Based on the results of both tests, it can be concluded that the HB variable does not significantly influence the USS variable.

H7: Hedonic Motivation (HEM) influences BEIN in adapting to AIKU. The results are consistent with the HEM to USS path, which has a strong coefficient of determination ($R2= 0.69$). However, after conducting the Path coefficient test, the result (-0.15) indicates that Hypothesis H7 (HEM → BEIN) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 0.675, less than 1.96. According to Ghozali (2008), the hypothesis is considered insignificant if the T-statistic is less than 1.96. Based on the results of both tests, it can be concluded that the HEM variable does not significantly influence the BEIN variable.

H8: Performance Expectancy (PEXP) influences BEIN in adapting to the use of AIKU. The results are consistent with the PEXP to BEIN path, which has a strong coefficient of determination (R2= 0.394). After conducting the Path coefficient test, the result (0.383) indicates that the Hypothesis (PEXP → BEIN) is accepted. Hypothesis testing using the t-Test with bootstrapping also resulted in 3.112, which is greater than 1.96. According to Ghozali (2008), the hypothesis is considered significant if the T-statistic is greater than 1.96. Based on the results of both tests, it can be concluded that the PEXP variable significantly influences the BEIN variable.

H9: Price Value (PRV) has an influence on BEIN in adapting to the use of AIKU. The results are consistent with the HEM to USS path, which has a strong coefficient of determination (R2= 0.69). However, after conducting the Path coefficient test, the obtained result (-0.131) indicates that Hypothesis H9 (PRV → BEIN) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 0.624, which is less than 1.96. According to Ghozali (2008), if the T-statistic is less than 1.96, the hypothesis is considered not significant. Based on the results of both tests, it can be concluded that the PRV variable does not significantly influence the BEIN variable.

H10: Social Influence (SOI) influences BEIN in adapting to the use of AIKU. The results are consistent with the SOI to USS path, which has a strong coefficient of determination (R2= 0.69). However, after conducting the Path coefficient test, the result (-0.108) indicates that Hypothesis H10 (SOI → BEIN) is rejected. Hypothesis testing using the t-Test with bootstrapping also resulted in 0.655, less than 1.96. According to Ghozali (2008), if the T-statistic is less than 1.96, the hypothesis is considered not significant. Based on the results of both tests, it can be concluded that the SOI variable does not significantly influence the BEIN variable.

Based on the research findings, it can be concluded that BEIN and PEXP have a significant influence on USS and BEIN in adapting to the use of AIKU. This is indicated by the strong coefficient of determination (R2) and the t-Test value greater than 1.96. Therefore, Hypotheses H1 and H8 are accepted.

On the other hand, EEX, FC, HB, HEM, PRV, and SOI do not have a significant influence on BEIN or USS in adapting to the use of AIKU. Although they have a strong coefficient of determination (R2), the t-Test values for these hypotheses are less than 1.96. Therefore, Hypotheses H2, H3, H4, H5, H6, H7, H9, and H10 are rejected.

In this context, the research findings indicate that BEIN and PEXP are the most significant factors in influencing the User Satisfactionof AIKU. On the other hand, other factors such as EEX, FC, HB, HEM, PRV and SOI do not have a significant influence. Therefore, researchers should consider the impact of BEIN and PEXP more prominently in future research and the development of AIKU applications.

4. CONCLUSION

The findings of this study offer valuable insights into the factors within the UTAUT2 model that influence Behavioral Intention (BEIN) and User Satisfaction (USS) in the usage of AI-based air quality detection applications. By focusing on the Indonesian context, this research not only addresses specific local challenges but also provides a framework that can be applied in various global contexts. The implications of this study are significant for the broader adoption of AI technologies in environmental monitoring, offering a model that can be adapted to different socio- economic and environmental settings, thereby enhancing global efforts to combat air pollution. Behavioral Intention (BEIN) and Performance Expectancy (PEXP) have been found to have a significant impact on the usage of the AIKU application, while Effort Expectancy (EEX), Facilitating Conditions (FC), Habit (HB), Hedonic Motivation (HEM), Price Value (PRV), and Social Influence (SOI) did not show a significant influence. The crucial role of Behavioral Intention (BEIN) indicates that users' intention to use the application is a key factor influencing their User Satisfaction . Meanwhile, Performance Expectancy (PEXP) also has a significant impact, reinforcing the notion that users' expectations of application performance are crucial in shaping their intention to use it. These findings provide valuable insights for application developers, who should consider the influence of Behavioral Intention and Performance Expectancy when designing and promoting the AIKU application. Recognizing the importance of these factors can help in designing more effective strategies to enhance users' intention and User Satisfaction of the application. Academically, this study makes a meaningful contribution to the literature by applying and validating the UTAUT2 model in a relatively new context, namely AI-based air quality detection applications. Further research is highly recommended to test these findings in various contexts and samples and to explore other factors that may impact the intention and user satisfaction of the AIKU application.

5. FUTURE WORK AND ACKNOWLEDGEMENTS

The findings of this study provide important insights into how the factors in the UTAUT2 model influence Behavioral Intention (BEIN) and User Satisfaction (USS) in the usage of the AI-based air quality detection application, AIKU. Behavioral Intention (BEIN) and Performance Expectancy (PEXP) have been found to impact the usage of the AIKU application significantly. At the same time, Effort Expectancy (EEX), Facilitating Conditions (FC), Habit (HB), Hedonic Motivation (HEM), Price Value (PRV), and Social Influence (SOI) did not show a significant influence.

The crucial role of Behavioral Intention (BEIN) indicates that users' intention to use the application is an essential factor influencing their User Satisfaction (USS). Meanwhile, Performance Expectancy (PEXP) also has a significant impact, reinforcing that users' expectations of application performance are critical in shaping their intention to use it. These findings provide valuable insights for application developers, who should consider the influence of Behavioral Intention and Performance Expectancy when designing and promoting the AIKU application. Recognizing the importance of these factors can help develop more effective strategies to enhance users' intention and User Satisfaction of the application. Academically, this study makes a meaningful contribution to the literature by applying and validating the UTAUT2 model in a relatively new context, namely AI-based air quality detection applications. Further research is highly recommended to test these findings in diverse global contexts and to explore additional factors that may impact the intention and user satisfaction of AI-based air quality detection applications. Expanding the research to include a comparative analysis across different countries and regions will provide a deeper understanding of how cultural, economic, and environmental factors influence the adoption and effectiveness of AI technologies in addressing air quality challenges.

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