Enhancing AIKU Adoption: Insights from the Role of Habit in Behavior Intention

Irwan Sembiring[1], Untung Rahardja[2], Danny Manongga[3], Qurotul Aini[4*], Abdul Wahab[5]
[1,3]Department of Information Technology, Satya Wacana Christian University, Indonesia [2]Department of Information, University of Technology Malaysia, Malaysia [4]Department of Information, University of Raharja, Indonesia [5]Department of Computer Science, International Islamic University Malaysia, Malaysia
[1]irwan@uksw.edu, [2]rahardjauntung@graduate.utm.my, [3]danny.manongga@uksw.edu, [4]aini@raharja.info [5]abdulwahab@iium.edu.my
***Corresponding Author**

Article Info

Article history:

Submission Nov 29, 2023
Revised Feb 20, 2024
Accepted March 22, 2024
Published March 31, 2024

Keywords:

AIKU
Air Quality
HT
BIN
UTAUT2

ABSTRACT

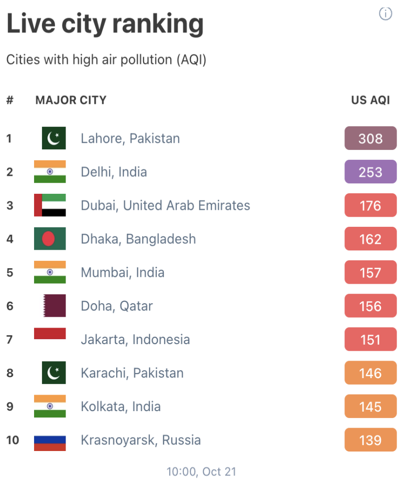
This **research focuses** on exploring and understanding the role of Habit in sustaining the adoption and continuous use of AIKU technology as its **primary objective**. The UTAUT2 model was chosen, emphasizing the Habit variable (HT) along with 6 other key variables: Performance Expectancy (PEX), Effort Expectancy (EEX), Price Value (PV), Social Influence (SIN) on Behavioral Intention (BIN), and User Behavior (UB), with the addition of **external variables** Perceived Risk (PR) and **moderating** Gender and Experience. The **research methodology** involves data analysis using **SmartPLS 4.0 software** and the **UTAUT2 model** as the framework and theoretical foundation. Survey data were collected from 414 AIKU users in Indonesia. **Findings** based on data analysis indicate that factors such as PE, EE, and PV **significantly positively** influence BI to continue using AIKU. In addition to filling **gaps** in knowledge regarding the role of Habit in air quality technology literature, another finding is that H **significantly positively** influences BIN and UB, while BIN **significantly positively** influences UB. This research's **novelty and primary contribution** lie in the implications concerning the crucial emphasis on the Habit factor in sustaining AIKU usage. The **development implications** underscore the importance of psychological factors in technology acceptance and retention, providing valuable insights for future strategy and policy development. **Limitations** of this research lie in the focus on the AIKU system affecting result generalization. **Future research**, expanding coverage, considering air quality system variations, employing diverse data collection methods such as in-depth interviews are recommended.

****Corresponding Author:***

Qurotul Aini (aini@raharja.info)
DOI: https://doi.org/10.34306/att.v6i1.364

1. INTRODUCTION

Technology has played a crucial role in transforming the global paradigm of modern life. Technological advancements have generated significant innovations across various fields, including health and the environment [1]. Air quality, as one of the vital aspects of daily life, has also come under the spotlight in the context of technology [2]. Air quality is one of the important factors that influences human health and comfort [3]. Air quality can be influenced by various sources of pollutants, such as cigarette smoke, dust, mold, exhaust gases, and chemicals. Exposure to air pollutants can cause various health problems, such as eye, nose, and throat irritation, headaches, allergies, asthma, chronic lung disease, and even cancer [4]. According to the **World Health Organization** in 2019, poor air quality (air pollution) causes a total of 4.2 million premature deaths [5], [6]. This is one of the environmental problems that is currently receiving great attention. In 2019 in North America, respiratory and cardiovascular diseases were discovered as a result of air pollution [7]. In the same year it was discovered that particulate matter (PM2.5) had been exposed to around 85% of the population in Europe [8]. Apart from developed countries in the European region, the Asian region which consists of developing countries also experiences high levels of exposure to air pollution [9]. As in 2022, the metropolitan area in Thailand is widely known as the area with the most negative impacts on health diseases [10]. Figure 1 is data presented by the **IQAir World Air Quality** website and provides insight into live air quality conditions in various countries to date.



Live city ranking

Cities with high air pollution (AQI)

#	MAJOR CITY	US AQI
1	Lahore, Pakistan	308
2	Delhi, India	253
3	Dubai, United Arab Emirates	176
4	Dhaka, Bangladesh	162
5	Mumbai, India	157
6	Doha, Qatar	156
7	Jakarta, Indonesia	151
8	Karachi, Pakistan	146
9	Kolkata, India	145
10	Krasnoyarsk, Russia	139

10:00, Oct 21

Figure 1. Live Tracking Air Pollution 2023
(Source: https://www.iqair.com/)

Seeing this, we realize the importance of monitoring and controlling indoor air quality to keep it clean and healthy [11],[12]. Monitoring air quality reflects the crucial role of society in maintaining ecosystem balance and protecting human health. Good air quality is an important element for environmental sustainability and community welfare. AI-based air quality monitoring systems have become an innovative solution for monitoring and improving air quality in various environments, including educational institutions [13],[14]. Technology education has become the main pillar in developing understanding and application of technology in various aspects of modern life [15]. In the midst of rapid digital transformation, the integration of technology into education is becoming increasingly important. One area that is attracting attention is the use of artificial intelligence (AI)-based air quality systems in educational settings [16]. The use of AI technology in air quality systems promises to make a positive contribution to the health and productivity of students and teaching staff [17], [18]. However, maintaining the long-term use of this system still faces challenges. **In this context**, research on the role of habits in maintaining sustainable use of AI-based air quality systems needs to be analyzed in more depth by Greenpreneur to ensure positive impacts on the environment and human health.

AIKU

Figure 2. AIKU (Artificial Intelligence Kualitas Udara)

AIKU is an AI-based air quality monitoring system technology that can measure the concentration of indoor air pollutants, such as fine particulates (PM2.5) [19], carbon monoxide (CO), carbon dioxide (CO2), nitrogen dioxide (NO2), ozone (O3), and volatile organic compounds (VOC) [20], [21]. AIKU can provide accurate and timely information [22] about air quality and provide optimal solutions to improve it. However, despite their clear benefits, the literature has not fully explained why some users are able to maintain continued use of these systems. Research in recent years has increasingly highlighted this so that many studies have focused on considering the factors that influence user acceptance of Air Quality Monitor technology using the Technology Acceptance Model (TAM) [23] proposed by Davis et al [24]. Researchers have also focused on how factors such as perceived usefulness, perceived ease of use, social norms, and other factors included in the UTAUT [25]. This model proposed by Venkatesh [26] can influence how air quality monitoring applications can be accepted and used by users. There is a need to overcome several weaknesses contained in both the TAM and UTAUT models, so in 2012 Venkatesh brought it back UTAUT2 was designed by combining new elements that are broader and more comprehensive [27]. One of the strong reasons for implementing UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) is that this framework considers a wider range of factors that can influence technology acceptance, including emotional and psychological aspects that may not be fully covered in the models previous [28]. In the context of air quality monitoring, it is recognized that understanding how users respond to and accept monitoring technologies can be critical in ensuring that these solutions are used effectively and have a positive impact on air quality and human health [29].

Underpinning this research is the recognition of a research disparity, specifically in revealing the integral role of habits in maintaining and utilizing AIKU technology over the long term. The ongoing use of this technology is of utmost importance to ensure sustained benefits for the health and comfort of students and teaching staff. **Previous research** found that Habit has a negative influence on Intention to Use (β: 0.120, p-value 0.042) and Perceived Usability (β: 0.098, p-value 0.037). Despite the existence of models and theories like UTAUT2, which have been used to analyze the acceptance and usage of technology, there has been no study specifically expanding this model to accommodate habit factors influencing the sustainable use of air quality monitoring systems [30]. Innovapreneurs involved in the development and implementation of AIKU technology will bring the innovative perspective needed to overcome these challenges by using SmartPLS 4.0 as the tool for data analysis and hypothesis testing [31].

The structure of this study is as follows: In **Section II**, we study the Theoretical Background which includes aspects of the UTAUT2 Variables Habit (HT), Behavioral Intention (BIN), Use Behavior (UB), Performance Expectancy (PEX), Effort Expectancy (EEX), Price Value (PV), Social Influence (SIN)) and Hypothesis. **Section III** discusses research methods and research instruments. **Section IV** provides a complicated overview of managing the research flow to achieve research results. Starting with an explanation of data collection accompanied by a detailed explanation of the 414 respondents, including information such as Gender, Age and Experience. Next, we focus on evaluating measurement model testing and structural evaluation of the model. This segment includes analysis and discussion of the study, explores variables that demonstrated significant influence, and reveals the results of the multigroup analysis based on G, A, and E. To conclude the study, a summary of the research findings and implications is provided in **section V**. Also presents anticipated challenges signals a path for future investigation, which may naturally be pursued by the authors of this paper or other researchers interested in this area of study.

2. RELATED WORK

2.1. Air Quality

Air quality is a crucial aspect of environmental health, directly impacting the well-being of both ecosystems and human populations [32], [33]. The assessment and management of air quality have become increasingly important due to the rising concerns about the adverse effects of air pollution on public health and the environment [34]. Air quality is commonly evaluated based on the concentration of various air pollutants, including particulate matter (PM), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), ozone (O3), and volatile organic compounds (VOCs) [35]. These pollutants originate from diverse sources such as industrial activities, transportation, and natural processes, contributing to the complexity of air quality dynamics [36].

The adverse effects of poor air quality are well-documented and include respiratory and cardiovascular diseases, adverse impacts on ecosystems, and climate change [37]. Particulate matter, for instance, can penetrate deep into the lungs, leading to respiratory problems, while ground-level ozone is known to cause respiratory issues and other health problems [38]. Monitoring and assessing air quality involve the use of various instruments and techniques, including air quality indices, remote sensing technologies, and atmospheric modeling [39]. The integration of these methods provides a comprehensive understanding of the spatial and temporal variations in air quality, enabling effective decision-making for air quality management and policy development [40].

Researchers and environmental practitioners have conducted extensive studies to understand the sources, transport, and transformation of air pollutants [41]. These studies aim to identify key contributors to poor air quality and develop strategies to mitigate the impact of anthropogenic activities. In conclusion, the theoretical background of air quality encompasses a multidisciplinary approach, integrating knowledge from atmospheric science, environmental chemistry, and public health. Ongoing research in this area contributes to a better understanding of the complex interactions that govern air quality dynamics, in line with the Socialpreneur spirit that is not only concerned with financial profits but also facilitates the development of effective strategies to safeguard human and environmental health.

2.2. Behavioral Intention

Behavioral intention is a critical concept in the field of psychology and social sciences, providing insights into the cognitive processes that influence an individual's decision to engage in a specific behavior. Rooted in the Theory of Planned Behavior (TPB) and the Theory of Reasoned Action (TRA), behavioral intention serves as a proximal determinant of actual behavior According to the TPB, behavioral intention is shaped by three main factors: attitude, subjective norm, and perceived behavioral control [42]. Attitude reflects an individual's positive or negative evaluation of the behavior, subjective norm captures the perceived social pressure or approval related to the behavior, and perceived behavioral control pertains to the perceived ease or difficulty of performing the behavior [43].

These factors collectively contribute to the formation of behavioral intention, which, in turn, predicts and influences actual behavior. Numerous studies have applied the TPB to understand and predict various behaviors, such as health-related behaviors, environmental conservation, and consumer choices [44]. The TPB has proven to be a robust theoretical framework for understanding behavioral intention due to its ability to integrate cognitive, social, and motivational factors [45]. It acknowledges that individual intentions are influenced not only by personal beliefs and attitudes but also by social norms and perceptions of control over the behavior.

Research in the realm of behavioral intention has expanded to explore the role of additional factors, such as moral considerations, emotions, and past behavior, to enhance the predictive power of the theoretical framework. By understanding the determinants of behavioral intention, researchers and practitioners can develop targeted interventions and strategies to promote positive behaviors and discourage undesirable ones [46], including those driven by innovative entrepreneurs (Innovapreneurs) seeking to integrate AIKU technology into various aspects of daily life. In the context of AIKU research, the theoretical background of behavioral intention, especially related to the Theory of Planned Behavior, provides a comprehensive framework for understanding the psychological processes that drive individuals in decision-making and adopting behaviors related to the use of AIKU.

2.3. Use Behavior

Understanding use behavior, particularly in the context of technology or product adoption, is crucial for researchers and practitioners aiming to predict and influence user actions. Several theoretical frameworks contribute to the comprehension of use behavior, and one widely applied model is the Technology Acceptance Model (TAM). The Technology Acceptance Model, posits that users' intentions to use a technology are influenced by two primary factors: perceived usefulness and perceived ease of use. Perceived usefulness refers to the user's belief that the technology will enhance their performance or productivity, while perceived ease of use relates to the user's perception of the effort required to use the technology [47].

Extending TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporates additional factors such as social influence, facilitating conditions, and behavioral intention. Social influence reflects the impact of societal norms and the influence of others on an individual's decision to use technology, while facilitating conditions encompass the infrastructure and resources supporting technology use [48]. Moreover, the Diffusion of Innovations theory, proposed by Rogers, suggests that the adoption of innovations follows a bell curve, with categories ranging from early adopters to laggards. This model emphasizes the role of communication channels, social systems, and perceived attributes of innovations in shaping use behavior.

The understanding of use behavior is not limited to technological contexts. In various disciplines, including consumer behavior and healthcare, theories like the Theory of Planned Behavior and the Health Belief Model contribute to understanding and predicting use behavior related to products or health interventions [49]. Overall, the theoretical framework of usage behavior in the background of AIKU research involves various aspects, encompassing models and theories that consider cognitive, social, and contextual factors that may influence individual decisions in adopting and using AIKU technology or products.

2.4. SOTA of Habit

Table 1. State-of-the-Art (SOTA)

Title	Years & authors	Novelty	Method	Limitation
Use of 'habit'is not a habit in understanding individual technology adoption: a review of UTAUT2 based empirical studies	2019, Kuttimani Tamilmani, Nripendra P. Rana, Yogesh K. Dwivedi [50]	Understanding the concept of 'habit' in the context of technology adoption has long been a focus in the literature. However, this research offers a fresh perspective by exploring how UTAUT2 can provide a deeper understanding of technology adoption factors without overly relying on the concept of habit. It engages in a critical analysis of empirical studies based on UTAUT2 to highlight the extent to which the 'habit' concept may not be suitable in the context of technology adoption, proposing an alternative framework for comprehending individual technology adoption behavior.	A Systematic Review : Conducting a systematic review of literature on empirical studies that utilize UTAUT2 as the framework for understanding technology adoption. Critical Analysis: Undertaking a critical analysis of each study to assess the relevance of the 'habit' concept and identifying additional elements that may enhance the understanding of technology adoption. Development of an Alternative Framework: Based on the findings from the critical analysis, developing an alternative framework that can offer a better understanding of the factors influencing technology adoption without necessarily referring to 'habit.'	Potential limitations in availabledata from the reviewed empirical studies could influence the final conclusions. There might be variations in methodologies among the studies that could impact the consistency of the analysis.
Determining factors affecting the perceived usability of air pollution detection mobile application "AirVisual" in Thailand: A structural equation model forest classifier approach	2022, Ardvin Kester S. Ong, Yogi Tri Prasetyo, Poonyawat Kusonwattana , Klint Allen Mariñas, Nattakit Yuduang, Thanatorn Chuenyindee, Kirstien Paola. Robas, Satria Fadil Persada, Reny Nadlifatin [10]	This study investigates the perceived usability of the "AirVisual" mobile application for air pollution detection in Thailand, introducing a novel approach by employing a Structural Equation Model Forest Classifier. While previous research has explored usability factors in various contexts, the application of this specific model to assess factors influencing user perceptions in the context of air pollution detection applications is a unique contribution.	The research methodology involves the utilization of a Structural Equation Model Forest Classifier to comprehensively assess and analyze the factors influencing the perceived usability of the "AirVisual" mobile application in Thailand. This advanced statistical technique enables the integration of structural equation modeling with ensemble learning, providing a robust method to handle complex relationships and dependencies among variables.	Despite the innovative approach, certain limitations must be acknowledged. The effectiveness of the Structural Equation Model Forest Classifier relies on the availability and quality of data, and any constraints or biases within the dataset may impact the model's accuracy. Additionally, while the study focuses on the Thai context, cultural and regional variations might limit the generalizability of the findings to a broader audience.

Title	Years & authors	Novelty	Method	Limitation
		This approach allows for a more nuanced understanding of the complex interplay between variables affecting the perceived usability of such applications in a specific geographical context.	Through this method, the study aims to uncover the intricate web of factors affecting user perceptions of usability, offering a nuanced perspective that goes beyond traditional linear models	Furthermore, the dynamic nature of technology and user preferences poses a challenge, as the usability perceptions may evolve over time, potentially affecting the long-term relevance of the study's conclusions.
Influence of Environmental Information on Users' Purchase Intentions for Electric Two Wheelers	2021, Fei-Hui Huang [51]	This paper explores the novel dimension of the influence of environmental information on users' purchase intentions for electric two wheelers. While previous studies have investigated factors affecting the adoption of electric vehicles, this research delves specifically into the impact of environmental information on the purchase decisions related to electric two wheelers. The unique focus on this specific vehicle category allows for a more nuanced understanding of how environmental considerations shape consumer intentions, contributing valuable insights to the broader discourse on sustainable transportation.	To examine the influence of environmental information on users' purchase intentions for electric twowheelers, a mixed-method research design will be employed. Quantitative data will be gathered through surveys to measure the correlation between the exposure to environmental information and the likelihood of users intending to purchase electric two-wheelers. Additionally, qualitative insights will be gathered through interviews and focus group discussions to provide a deeper understanding of the nuanced factors and perceptions that underlie the quantitative findings. This combined approach aims to offer a comprehensive and detailed analysis of the complex interplay between environmental information and consumers' decisions to adopt electric two-wheelers.	Despite the comprehensive methodology, certain limitations must be acknowledged. The study's findings may be context specific and influenced by regional variations in environmental awareness and infrastructure. The self reported nature of survey data introduces the potential for social desirability bias, impacting the accuracy of responses. Moreover, the rapidly evolving landscape of electric vehicle technologies and the dynamic nature of consumer preferences pose challenges in capturing the most up to-date and representative data. Additionally, external factors such as government policies and economic conditions may influence purchase intentions and are factors that are challenging to control for in this study.
Factors Affecting E-Scooter Sharing Purchase Intention: An Analysis Using Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)	2021, Belinda Azzahra, Farhan Atha, Fathiyya Rizka, Rizki Amalia, Shafira Husna [52]	This study uniquely explores factors influencing users' purchase intentions in the E-Scooter sharing market, employing the UTAUT2 framework. Unlike previous research, the focus is specifically on determinants shaping users' willingness to purchase E-Scooter sharing services, contributing a nuanced perspective to this dynamic market.	To unravel these factors, a quantitative approach using surveys will be employed. Key UTAUT2 constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions will be measured. Statistical analyses, including regression models, aim to assess the significance of these factors in predicting purchase intentions.	Acknowledging potential limitations, the study considers context dependency, reliance on self-reported survey data, and the dynamic nature of the shared mobility market. Despite these challenges, the research aims to provide valuable insights into the evolving landscape of shared mobility services.
Determinants of customer intentions to use electric vehicle in Indonesia: An integrated model analysis	2022, Indra Gunawan, Anak Agung Ngurah Perwira Redi, Ahmad Arif Santosa, Meilinda Fitriani Nur Maghfiroh, Andante Hadi Pandyaswargo,	This study innovatively explores determinants influencing customer intentions to use electric vehicles (EVs) in Indonesiathrough an integrated model analysis. By synthesizing various factors into a cohesive model,	The research employs a quantitative approach, utilizing surveys to gather data on environmental attitudes, perceived benefits, and socio demographic variables. Structural equation modeling (SEM) is	Acknowledging potential constraints, the study considers cultural variations, the dynamic nature of technology adoption, and potential biases in self reported survey data.

	Adji Candra Kurniawan [53]	model, the research contributes unique insights to the understanding of EV adoption in the Indonesian context.	The research employs a quantitative approach, utilizing surveys to gather data on environmental attitudes, perceived benefits, and socio demographic variables. Structural equation modeling (SEM) is	Acknowledging potential constraints, the study considers cultural variations, the dynamic nature of technology adoption, and potential biases in self reported survey data.
The effect of internet searches on afforestation: The case of a green search engine	2018, Pedro Palos-Sanchez, Jose Ramon Saura [54]	This study innovatively explores the impact of a green search engine on afforestation, diverging from previous research on the broader link between online activities and environmental awareness.	Utilizing a quantitative approach, the research analyzes data from the green search engine to understand user queries related to afforestation and their correlation with actual afforestation initiatives. Surveys may supplement this data to capture user perceptions, providing a comprehensive perspective on the role of internet searches in promotingafforestation.	The study acknowledges potential limitations, including the context specific nature of findings, challenges in establishing direct causation between internet searches and afforestation outcomes, and the influence of external factors on afforestation efforts.
Sustainable road transportation adoption research: A meta and weight analysis, and moderation analysis	2023, Vedant Singh, Tej Singh, Elena Higueras Castillo, Francisco Jose Liebana Cabanillas [55]	This study introduces a unique approach to sustainable road transportation adoption research by employing meta and weight analysis alongside moderation analysis. Unlike prior studies, this research combines these methods to offer a comprehensive perspective on the current state of the field, aiming to contribute valuable insights.	The methodology involves a metaanalysis to integrate existing research on sustainable road transportation adoption, utilizing weight analysis for study significance. Moderation analysis will explore contextual and demographic factors' potential impact on determinants of sustainable transportation adoption.	Acknowledging constraints, the study considers variations in methodologies and sample characteristics in synthesizing diverse studies. The effectiveness of the analysis relies on the available data's quality and scope, and moderation analysis may be limited by data constraints. Despite these considerations, the research aims to provide a holistic understanding of sustainable road transportation adoption.

3. METHODS

This research was conducted using a **quantitative approach** with the research design depicted in Figure 3.

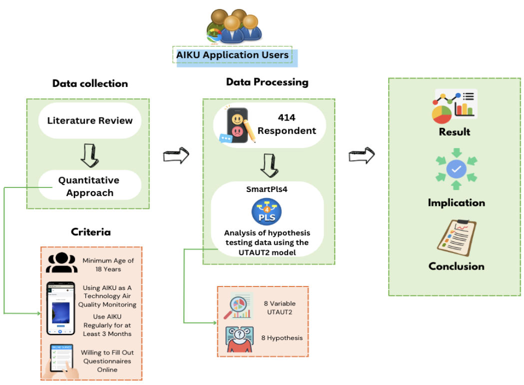


Figure 3. Research Design

The design integrates the UTAUT2 theoretical framework with the concept of habit as a factor influencing the adoption and sustainable use of AIKU as an air quality monitoring system. The research design depicted illustrates a quantitative methodological flow divided into three main stages. Initially, there is the data collection stage, commencing with a literature review to identify theoretical foundations and existing research gaps. Subsequently, statistical data collection from respondents is conducted through an **online survey** using Google Forms, containing questions designed to measure variables within the expanded UTAUT2 model, incorporating the habit variable. Online surveys were chosen for their broader reach, quicker response, cost-effectiveness, and ease compared to conventional survey methods. **The criteria** are as follows: (1) Minimum age of 18, (2) Use of AIKU as an AI technology-based air quality monitoring system at home, workplace, or elsewhere, (3) Regular use of AIKU for a minimum of 3 months, (4) Willingness to fill out the questionnaire online, (5) Consent for the questionnaire data to be further processed by the researcher.

The data obtained in Figure 5 represents the results of conducted over **5 months** (January 2023 - May 2023). The total number of respondents reached 439, but only **414 respondents** met the criteria for data validity according to the established standards. The data was then analyzed using SmartPLS 4.0 software with the partial least squares structural equation modeling (PLS-SEM) technique to test hypotheses and identify relationships between variables [56]. The 25 data points that did not meet these criteria were excluded/ignored, ensuring that the data to be further processed is of high quality and can provide accurate insights into the researched data. In the final stage of the research during the findings presentation phase, various statistical results and data analyses may be included. The impact of these findings is then translated into more general applications, concluding and suggesting directions for future research or practical usage. This research pathway reflects a systematic and continuous process, often adopted in social and business studies, particularly in the context of user adaptation to technological innovations.

3.1. Research Instruments

Comprising two sections, the first part focuses on respondent identification, encompassing inquiries about age and experience in using the AI air quality system. **The research population** consists of AIKU system users in Indonesia. Moving to the second part, it delves into the research variables, addressing questions about the **7 UTAUT2 variables, 1 external variable, and 2 moderating variables**. The research statement utilizes a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Within each variable, there are multiple indicators defining relevant aspects. Indicators within the HT variable pertain to the habit of automatic system usage, while the Behavioral Intention variable contains indicators measuring the intent to continue using the system in the future. Other variables also feature indicators portraying specific aspects related to perceptions and the use of the AIKU system. The data analysis for this research employs **the partial least squares structural equation modeling (PLS-SEM) technique**, facilitated by **smartPLS 4.0** software, where constructs are visualized in Figure 4. PLS-SEM is utilized to test research hypotheses concerning the simultaneous and partial relationships between research variables.

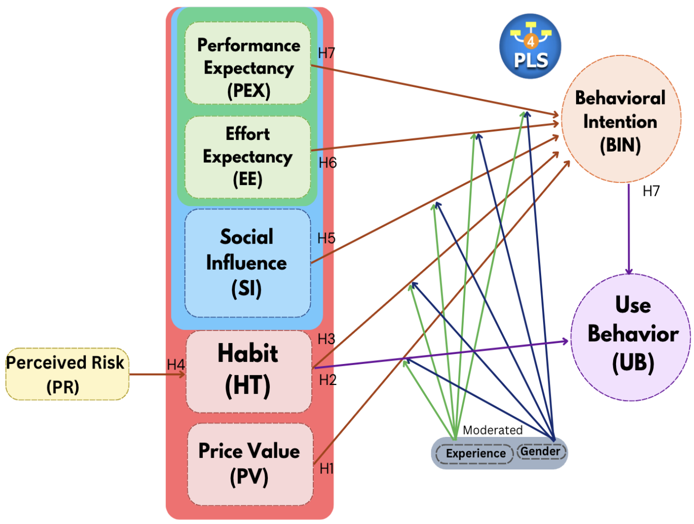


Figure 4. Construct of the UTAUT2 variable using smartpls4

Through an approach that integrates the UTAUT2 theory with the habit concept, factors influencing the sustenance of AI-based air quality system usage in the educational environment are examined to provide a more holistic understanding. The variables utilized are HT, BIN, UB, PEX, EEX, PV, SIN as the 7 main variables of UTAUT2, and PR as an external variable. G & E are added as moderating variables **to observe** how gender and experience level differences can moderate the impact of the main variables on maintaining the use of AI-based air quality systems in the educational environment. Two other UTAUT2 variables, Facilitating Condition and Hedonic Motivation, along with **Age, are not included** because the primary focus of this research is on factors that sustain system usage. In this research focus, both aspects are considered less relevant or less crucial in explaining how system usage can be maintained. The research findings contribute to the development of more effective educational technology adoption strategies, particularly in sustaining technology adoption in educational institutions.

3.2. Habit (HT) in the UTAUT2 Model

Habit is one of the factors that plays an important role in the UTAUT2 model. Habit is defined as behavior that is repeated consistently [57]. In the context of acceptance and use of technology, habit refers to the extent to which individuals have accustomed themselves to the use of a particular technology [58]. Habit's **strong influence** on technology use is because habits that become habits typically require less effort and lack cognitive inhibition. This is proven by many related studies, [59] shows a **strong significant** level of Habit towards Behavioral Intentions to use Mobile technology among the other 2 accepted variables, [60] The relationship between Habit and Intention to adopt Mobile Internet shows**positive significance**, Habit **very strong significance** in predicting teachers' Behavioral Intentions to use mobile internet, [50] and [28] shows that "habit" has a **significant influence** on usage intention and behavior, even stronger than other main constructs of UTAUT2.
H1: Habit has a positive and significant influence on Behavioral Intention in using the AI air quality system.
H2: Habit has a positive and significant influence on Use Behavior in using the AI air quality system.

3.3. Performance Expectancy (PEX) in the UTAUT2 Model

Performance Expectancy is a key factor in technology adoption intention that measures the extent to which technology helps users [61]. Perceived benefits are the belief that technology improves performance, PE outcome expectations include anticipation of the consequences of individual behavior, Job suitability is related to increased performance. Relative advantage compares the benefits and costs of a technology. Performance expectations **influence** the intention to use technology as a whole [62]. [27] define performance expectations as the extent to which users anticipate gaining benefits from the system. This concept is strongly supported by [63], who found a **substantial correlation** between performance expectations and user intent to utilize diabetes management apps among patients. [64] investigation underscored the **important role** of performance expectations as the only influential factor influencing users' adoption of third-party payment platforms. In the context of this research, considering the relevance of its application to AIKU, it is stated that:
H3: Performance Expectancy has a positive and significant influence on Behavioral Intention in using the AI air quality system.

3.4. Effort Expectancy (EE) in the UTAUT2 Model

[65] explains the **important role** of effort expectancy in influencing intention and use, especially in the context of technology ease of use. Furthermore, [66] demonstrated the **real influence** of effort expectations on mobile app utilization among food consumers. Thus, ease of use of AIKU can be assessed through the lens of effort expectancy, leading to the hypothesis that:
H4: Effort Expectancy has a positive and significant influence on Behavioral Intention in using the AI air quality system.

3.5. Social Influence (SIN) in the UTAUT2 Model

Individuals in the immediate social circle can have a favorable or unfavorable impact on the person. [67] shows how social influence **significantly influences** the tendency to use mobile transportation applications. Compatibility and a person's social network contribute positively to the persistence of mobile application use [68]. In this particular case, if people around an individual support the use of the 'AirVisual' app, it is likely that this will influence the individual's intention to use it as well. So the AIKU hypothesis takes the form:
H5: Social Influence has a significant effect on Behavioral Intention.

3.6. Price Value (PV) in the UTAUT2 Model

Consumers are typically responsible for bearing the financial costs associated with technology use, which include device-related expenses, data costs, and service costs [69]. These financial dimensions and pricing structures can have a **significant impact** on technology adoption among consumers [70]. In contrast, in the field of marketing research, the perceived value of a product or service is usually determined by its price, in addition to the quality of the product or service [16]. The favorable price-value effect becomes apparent when individuals believe that the benefits of using the technology outweigh the associated financial costs [71]. As a result, a **positive effect** on intentions regarding price value is expected. Therefore, price value can be an indicator of Behavioral Intention to adopt mobile Internet technology [72]. Price value also shows a **significant impact** on intention to use [73].
H6: Price Value has a positive and significant influence on Behavioral Intention in using the AI air quality system.

3.7. Perceived Risk (PR) in the UTAUT2 Model

[74] highlighted the **important role** played by perceived risk and perceived trust as influential factors that shape user intentions when using mobile applications. Investigation [75] revealed a common practice in which individuals evaluate the potential risks associated with a system or technology before they choose to interact with it. Consequently, establishing trust among users is considered an important step before they show a willingness to accept the functionality of an application [76]. Based on this insight, the following AIKU research hypothesis:
H7: Habitual Behavior memediasi hubungan antara Perceived Risk dan Behavioral Intention.
H8: Behavioral Intention has a positive and significant influence on Use Behavior in using the AI air quality system.

From the research above, it can be seen that there are **gaps** that have been developed in this research and there are also not many previous air quality studies that have made **habit the main focus** in the UTAUT2 model. In previous research using the UAUT 2 model designed by Venkatesh, it was found that the ”AirVisual” mobile application in Thailand had a direct **negative influence** on HB which was significant on IU. Based on this, **the novelty** of the research is enriched by examining the role of ”habit” in influencing the acceptance and use of AI-based air quality monitoring systems at AIKU. So, the main aim of this research is to deepen the study to explore the role of habit in the specific context of using AIKU as an air quality monitoring system. AI can provide a valuable contribution to a more complete understanding of technology adoption.

4. RESULT

With a solid foundation from the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) theoretical framework, the next step that will be taken in this research is to reveal the implications and important findings that have been obtained through careful data analysis. By examining the UTAUT2 construct which has been expanded to include habit factors, this research can provide in-depth insight into the role of habits in influencing the adoption and sustainable use of AI-based air quality systems (AIKU) in educational environments.

4.1. Data collection

The results of the Online Survey conducted over **5 months** (January 2023 - May 2023) showed a total of 439 respondents. However, **only 414 respondents** met the data validity criteria according to the established standards. These results were then visualized in Figure 5. Visualizes several categories such as gender, age range, and the usage of AIKU. In terms of **gender**, 221 respondents were male (53.38%), while 193 respondents were female (46.62%). The **age** range is also divided with 199 respondents (18 - 27), 92 respondents (28 - 37), 100 respondents (39 - 47), and 23 respondents (48 - >50). The majority of respondents, 402 respondents (97.10%), **have used AIKU**, while only 9 respondents (2.17%) have not used it. In terms of **using AIKU regularly for 3 months**, 399 respondents (96.38%) indicated that they use it regularly, while 15 respondents (3.62%) admitted not using AIKU regularly. **Out of 25 data** points that did not meet these criteria, they were excluded/ignored. This ensures that the data to be further processed is of high quality and can provide accurate insights into the researched data. The analysis conducted includes the evaluation of the Measurement Model with PLS Algorithm and the Structural Model Evaluation (Inner Model) using Bootstrapping.

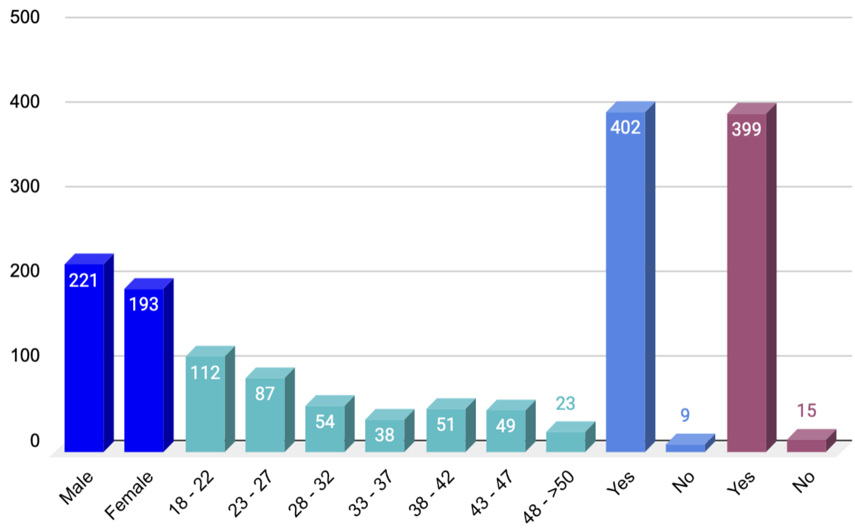


Figure 5. Online Survey Results

4.2. Evaluation of Model Measurements (Outer Model)

An important component in factor analysis is the initial stage in research data analysis which focuses on measuring the variables used in the model in understanding the relationship between the latent variables being measured and the construct (indicator block). The measurement analysis process for this model was carried out using the PLS Algorithm in SmartPLS 4.0. The measurement analysis stages of this model are the **Outer Loading Test, Reliability Test using Cronbach's alpha and Composite Reliability (CR), AVE Convergent Validity Test, R-squared & GOF Test and, Indexand Discriminant Validity Test.**

4.2.1. Outer Loading Test

The Outer Loading test is used to evaluate the extent to which the indicators (measurement variables) used in the model have a strong relationship with the construct (latent variable) being represented. The expected outer loading value is >0.5 or ideally >0.7. In this study, the outer loading results are shown in Table **??**.

Table 2. Outer Loading Results

Indicator	Outer loadings	Indicator	Outer loadings	Indicator	Outer loadings
BIN1 ← BIN	0.863	EE4 ← EE	0.739	PR1 ← PR	0.921
BIN2 ← BIN	0.842	HT1 ← HT	**0.877**	PR2 ← PR	0.928
BIN3 ← BIN	0.873	HT2 ← HT	**0.88**	PV2 ← PV	0.854
BIN4 ← BIN	0.73	HT3 ← HT	**0.878**	PV3 ← PV	0.914
EE1 ← EE	0.847	HT4 ← HT	**0.824**	SIN1 ← SI1	1
EE2 ← EE	0.822	PEX1 ← PEX	0.888	UB1 ← UB	0.877
EE3 ← EE	0.82	PEX2 ← PEX	0.899	UB2 ← UB	0.88

The results of this test show that **HT** and other indicators dominate with **strong outer loading** values, with a value range of 0.739 - 1, this shows that these indicators measure the variability of the relevant constructs well. There is an indicator (PV1) with an **outer loading value below** the threshold, namely ≥0.70. After much consideration, the researchers decided to **eliminate the PV1 Indicator**. By eliminating these indicators, the structure of the research model will experience changes, both in the relationships between variables and in the results of the analysis. These changes can include changes in path coefficients between variables, changes in the interpretation of results, as well as impacts on the overall model. This step was taken to **increase** the validity and reliability of the research model.

4.2.2. AVE Validity Test & Cronbach's alpha Reliability Test, Composite Reliability (CR)

These two tests were carried out as an important step in data analysis **to ensure** that the survey instruments used in the research were of **good quality and reliable**. At the validity test stage, the aspect that needs to be checked is convergent validity where the "Average Variance Extracted" (AVE) value for each construct should be >0.5 and the Reliability Test of indicators and constructs is checked by looking at the Cronbach's alpha and Composite Reliability (CR) values, shown in Table 3.

Table 3. Validity & Reliability Test Results

Variable	Average Variance Extracted (AVE)	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)
BIN	0.687	0.847	0.856	0.897
EE	0.653	0.823	0.835	0.883
HT	0.748	0.888	0.889	0.922
PEX	0.798	0.747	0.748	0.888
PR	0.856	0.831	0.832	0.922
PV	0.782	0.725	0.755	0.877
UB	0.772	0.705	0.705	0.871

The results of the convergent validity test in table 2 show that HT has an AVE value of 0.748, a Cronbach's alpha value of 0.886, a Composite Reliability (rho_a) value of 0.888, and a Composite Reliability (rho_c) value of 0.921. Meanwhile, other constructs "BIN," "PEX," "PV," "EE," "PR" and "UB" also have Average Variance Extracted (AVE) values >0.5 which indicates that the indicators used to measure These constructs significantly reflect the construct being measured, meaning that all variables are declared **acceptable**. Not only that, this construct also has a **good level** of reliability with values that exceed the generally accepted thresholds, namely Cronbach's alpha and Composite Reliability (CR) of more than 0.7 (>0.7). The reliability values in the table reflect the level of consistency and reliability in construct measurement. This means that the **measurement** of these constructs is considered to have a good level of consistency and reliability, and is declared acceptable so that the data is considered reliable in further analysis.

4.2.3. Discriminant Validity Test

To test discriminant validity, there are two ways to check cross loading. First, cross loading between indicators compares the relationship between the indicators and their constructs and the other constructs presented in Table 4.

Table 4. Discriminant Validity Results in Cross loading

Variable	BIN	EE	H	PEX	PR	PV	SI1	UB
BIN1	**0.863**	0.666	0.734	0.697	0.696	0.707	0.575	0.721
BIN2	**0.842**	0.632	0.698	0.638	0.634	0.603	0.558	0.66
BIN3	**0.873**	0.62	0.752	0.642	0.733	0.674	0.571	0.703
BIN4	**0.73**	0.583	0.616	0.529	0.536	0.509	0.537	0.564
EE1	0.673	**0.847**	0.685	0.76	0.643	0.599	0.648	0.631
EE2	0.627	**0.822**	0.697	0.668	0.566	0.598	0.577	0.599
EE3	0.636	**0.82**	0.626	0.624	0.596	0.53	0.57	0.6
EE4	0.477	**0.739**	0.541	0.541	0.453	0.471	0.58	0.481
HT1	0.738	0.669	**0.877**	0.662	0.677	0.691	0.628	0.725
HT2	0.738	0.713	**0.88**	0.706	0.717	0.654	0.667	0.703
HT3	0.748	0.692	**0.878**	0.705	0.701	0.664	0.592	0.717
HT4	0.706	0.67	**0.824**	0.568	0.626	0.589	0.605	0.65
PEX1	0.661	0.694	0.702	**0.888**	0.64	0.583	0.578	0.644
PEX2	0.694	0.749	0.666	**0.899**	0.635	0.602	0.648	0.653
PR1	0.733	0.656	0.711	0.641	**0.921**	0.664	0.564	0.685
PR2	0.727	0.649	0.744	0.678	**0.928**	0.71	0.577	0.745
PV2	0.581	0.567	0.624	0.524	0.586	**0.854**	0.494	0.56
PV3	0.743	0.638	0.701	0.64	0.717	**0.914**	0.594	0.752
SIN1	0.675	0.733	0.72	0.687	0.617	0.62	**1**	0.67
UB1	0.696	0.552	0.71	0.618	0.677	0.58	0.557	**0.877**
UB2	0.713	0.713	0.711	0.658	0.683	0.742	0.62	**0.88**

The results shown in Table 4 show that each HT measurement indicator (H1, H2, H3, H4) has a **higher correlation** with the Habit construct variable than it correlates with other construct variables. Overall, each indicator of one construct **has a higher** cross loading than the other constructs. By examining this table, researchers can ensure that different constructs are truly independent, validate discriminant validity in the measurement model, and maintain the integrity of data analysis. Second, Fornell-Larcker compared the AVE root value with the correlation between constructs presented in Table 5.

Table 5. Discriminant Validity Results for Fornell-Larcker

	BIN	EE	HT	PEX	PR	PV	SIN	UB
BIN	**0.829**							
EE	0.754	**0.808**						
HT	0.827	0.793	**0.865**					
PEX	0.759	0.806	0.765	**0.893**				
PR	0.789	0.706	0.787	0.713	**0.925**			
PV	0.757	0.684	0.752	0.664	0.743	**0.884**		
SIN	0.675	0.733	0.72	0.687	0.617	0.62	**1**	
UB	0.802	0.72	0.808	0.726	0.774	0.752	0.67	**0.879**

The results show that the AVE root value for HT is 0.865 **greater** than the correlation with the construct variables PEX, PV, SIN, and US. This means that discriminant validity for the HT variable has been **fulfilled**. Likewise with the AVE root value of other variables which is shown on the diagonal line, where the results **exceed the correlation** between the construct and other constructs on the vertical and horizontal lines. The results of the two-stage cross loading examination confirm that the discriminant validity test in this study was successful, showing that the constructs in the model are truly **independent** of each other.

4.2.4. R-squared test and GOF Index

R-squared (coefficient of determination) is used to measure the extent of the variance of the dependent variable and provide an indication of the model's success in explaining data variability, the results are presented in Table 6.

Table 6. R-square (R2 Value)

Variable	R-square	R-square adjusted
BIN	0,754	0,751
US	0,740	0,739

BIN and US show the extent to which the model can explain variations in both. In the BIN variable, R2 of **0.754** indicates that around **75.4%** of the variation in Behavioral Intention can be explained by the variability and influence of the independent variables in the model. The adjusted R-squared value for the BIN variable is **0.751**, accommodating the number of independent variables in the model. In the US variable, R2 of 0.740 indicates that around **74.0%** of the variation in Use Behavior can be explained by the variability and influence of the independent variables in the model, with an adjusted R-squared value of **0.739.** Apart from R-square, the assessment of the structural equation model in SEM-PLS can also be determined by testing the goodness-of-fit value, the results of which are visualized in Table 7.

Table 7. Result of GOF=$\sqrt{}$(AVE x R^2

Average		Result
AVE	0.757	Average AVE Average R^2
R2	0.75	$\sqrt{}$(AVE x R^2

Average AVE value is 0.757, this construct shows high reliability. Meanwhile, Average R^2 with a value of 0.75 indicates a satisfactory explanation. The Average AVE * Average R^2 result is 0.565. With a GOF result of **0.752**, this shows that the Goodness-of-Fit test is above the high threshold. This means that the empirical data from this research is **very suitable** for model measurement, showing a high level of quality, and has significant predictive power compared to standard values.

4.3. Structural Model Evaluation (Inner Model)

In this stage, the research focus is on understanding how these variables are interconnected and influence each other in the research model. The analysis will test the hypotheses and causal relationships between the specified variables. Using the Bootstrap technique generates a sampling distribution of structural model estimates that allows for measuring uncertainty in the model parameters and hypothesis testing results, which are presented in Figure 6.

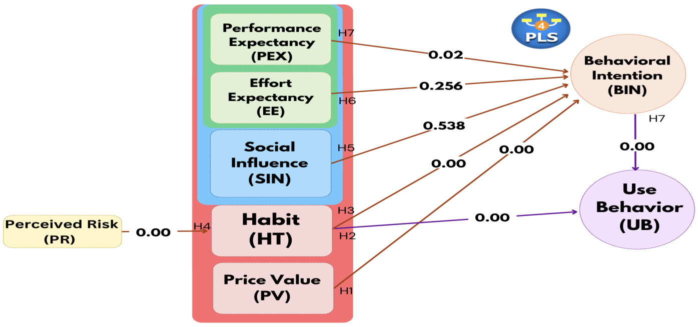


Figure 6. Bootstrap technique measurement results

The Figure illustrates the measurement results to assist researchers in evaluating the extent to which their model is consistent with stronger and more reliable outcomes.

4.3.1. Hypothesis Testing / Structural Model Testing

The results of this test were obtained through a bootstrapping process, which focuses on the path coefficient values shown in Table 8.

Table 8. Path Coefficient Results of Bootstrap technique

Hyp.	Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-statistics	p-value	Influence	Result
H1	HT → BIN	0.473	0.471	0.057	8.317	0	Significant	Accepted
H2	HT → UB	0.457	0.455	0.066	6.978	0	Significant	Accepted
H3	PEX → BIN	0.182	0.182	0.058	3.152	0.002	Significant	Accepted
H4	EE → BIN	0.059	0.062	0.052	1.135	0.256	Not Sig	Rejected
H5	SIN → BIN	0.028	0.028	0.045	0.615	0.538	Not Sig	Rejected
H6	PV → BIN	0.223	0.223	0.052	4.309	0	Significant	Accepted
H7	PR → HT	0.787	0.786	0.026	3.412	0	Significant	Accepted
H8	BIN → UB	0.415	0.416	0.065	6.381	0	Significant	Accepted

In accordance with the stipulated criteria, a hypothesis is deemed acceptable if the Original Sample value approaches +1, the t-statistic exceeds 1.96 (>1.96), and the pValue is less than 0.05 (<0.05). The outcomes presented in Table 8 lead to the following conclusions regarding the hypotheses:

H1, H3, & H7 indicate a significant positive influence of H, PEX, PV on BIN, with Original Sample values of 0.473, 0.182, 0.787, t-statistics (> 1.96) 8.317, 3.152, 4.309, and pValues (< 0.05) 0, 0.002, 0. Consequently, all three hypotheses are **accepted**.

H2 & H8 demonstrate a significant positive influence of H & BIN on UB, with Original Sample values of 0.457 & 0.415, t-statistics (> 1.96) 6.978 & 6.381, and pValues (< 0.05) 0 & 0. Therefore, both hypotheses are **accepted**.

H6 indicates a significant positive influence of PR on H, with an Original Sample value of 0.223, t-statistic (> 1.96) 3.412, and pValue (< 0.05) 0. Hence, this hypothesis is **accepted**.

These **findings** suggest that Habit has a positive and significant impact on their intention to adopt the AIKU system, as well as User Behavior towards the AIKU system. This discovery represents a **novelty** and a significant **contribution** to this research, underscoring the importance of understanding the role of habits in driving the acceptance and use of AIKU air quality technology.

4.3.2. Analysis of Moderating Variables Gender and Experience

Table 9. Experience Moderation Results

	Original	Mean	STDEV	t value	p value
Variable	Use Experience >3 Months				
BIN ->UB	**0.418**	0.418	0.066	6.286	**0**
EE ->BIN	**0.053**	0.055	0.054	0.973	0.331
HT ->BIN	**0.477**	0.474	0.059	8.057	**0**
HT ->UB	0.455	**0.455**	0.067	6.78	**0**
PEX ->BIN	0.176	**0.176**	0.059	2.979	**0.003**
PR ->HT	0.793	**0.792**	0.025	31.309	**0**
PV ->BIN	0.223	**0.223**	0.054	4.149	**0**
SIN ->BIN	0.034	0.035	**0.048**	0.719	0.472
Variable	Use Experience <3 Months				
BIN ->UB	0.087	0.091	0.582	0.15	0.881
EE ->BIN	0.23	0.264	0.685	0.336	0.737
HT ->BIN	0.68	0.672	0.714	0.952	0.341
HT ->UB	0.75	0.756	0.538	1.394	0.163
PEX ->BIN	0.14	0.111	1.786	0.078	0.938
PR ->HT	0.684	0.714	0.163	4.189	**0**
PV ->BIN	0.095	0.098	1.508	0.063	0.95
SIN ->BIN	-0.237	-0.253	0.994	0.238	0.812

In the context of AIKU users who have more than 3 months of experience, user experience plays an important role as a moderator in several relationships. Among these experienced users, user experience acts as a moderator in the relationship between PEX $\rightarrow$ BIN. In other words, the longer users use AIKU, the greater the influence of these variables on their intention to continue using the system. In contrast, in the new AIKU user group, user experience did not memorize any variables. This suggests that new users may not feel much influence from other factors. If analyzed more deeply, even though experience does not affect the PR-H relationship, it could indicate that newcomers are more careful and consider risks before forming habits related to AIKU.

Table 10. Experience Moderation Results

	Original	Mean	STDEV	t-value	p value
Variable			Female		
BIN ->UB	**0.419**	0.423	0.088	4.79	**0**
EE ->BIN	**0.161**	0.166	0.083	1.94	0.052
HT ->BIN	**0.391**	0.389	0.08	4.861	**0**
HT ->UB	0.431	**0.426**	0.092	4.712	**0**
PEX ->BIN	0.155	**0.158**	0.092	1.687	0.092
PR ->HT	0.709	**0.708**	0.044	15.963	**0**
PV ->BIN	0.236	**0.227**	0.083	2.847	**0.004**
SIN ->BIN	0.027	0.029	**0.066**	0.403	0.687
Variable			Male		
BIN ->UB	0.408	0.408	0.099	4.118	**0**
EE ->BIN	-0.032	-0.036	0.067	0.535	0.592
HT ->BIN	0.54	0.55	0.081	6.778	**0**
HT ->UB	0.479	0.48	0.099	4.869	**0**
HT ->UB	0.479	0.48	0.099	4.869	**0**
PEX ->BIN	0.19	0.189	0.075	2.533	**0.011**
PR ->HT	0.847	0.849	0.027	31.201	**0**
PV ->BIN	0.225	0.22	0.062	3.516	**0**
SIN ->BIN	0.038	0.037	0.065	0.566	0.571

The results of the moderate analysis show that there are significant differences between male and female users. This difference influences the intentions of male and female users in using the AIKU system. For male users, there was a significant moderating effect on the PEX $\rightarrow$ BIN relationship (0.011), indicating that the more experienced the user, the greater the impact of PEX on his intentions. In contrast, female users show a moderating effect on the relationship PV $\rightarrow$ BIN (0.004) on female user intentions. This comparison shows. Male users are more influenced by experience, especially the PEX variable, while female users are influenced by the PV variable.

4.4. Research Analysis and Discussion

The data analysis results yield findings that provide in-depth insights into sustaining the adoption and usage of AIKU technology and the research hypotheses. Firstly, the findings affirm that variables HT, PEX, and PV have a **significant positive** impact on BIN, as explained in H1, H3, and H7. These results are reinforced by significant p-values (0, 0.002, 0), indicating that individuals with positive perceptions of these factors are more likely to have higher intentions to use AIKU. Furthermore, H2 and H8, stating a **significant positive** influence between variable H and BIN on User Behavior (UB), are also supported with significant p-values (< 0.05) (0, 0). These results confirm that user behavior can be positively predicted by satisfaction levels and users' intentions to continue using AIKU. In addition, the **significant positive** findings between PR and H (H6) with a significant p-Value value (< 0.05) (0) indicate that effective PR efforts can change user behavior in improving human factors so that desire will be formed in using AIKU in the long term. However, H4 and H5, assuming the non-significant impact of EE and SIN on BIN, lack support with p-values (< 0.05) (0.256, 0.538), suggesting that perceptions of External Effectiveness and Subjective Norms do **not significantly** contribute to forming user intentions.

The role played by **HT** in **H1** indicates that HT has a direct and **significant positive** influence on BIN, measured with a path coefficient of 0.473 and T-statistics reaching 8.317 with a p-value of 0. Therefore, **H1 is accepted**. This finding suggests that the stronger users' habits are in using AIKU, the higher their behavioral intentions to adopt the system. **H2** reaffirms the positive and significant direct role of HT, this time in its relationship with UB, measured with a positive path coefficient of 0.457 and T-statistics of 6.978 with a p-value of 0. Therefore, **H2 is accepted**. Thus, HT also exerts a **strong influence** on the extent to which users genuinely adopt and use AIKU in their daily actions. This finding contributes to the literature by emphasizing the crucial role of habit in shaping the intentions and behaviors of AIKU users. The strong interconnection between HT, BIN, and UB provides a foundation for more focused development and marketing strategies to enhance user trust in AIKU.

Significant insights regarding the impact of **PEX on BIN**, with a path coefficient of 0.182, indicate that higher performance expectations increase the likelihood of user adoption of AIKU. Statistical support from T-statistics of 3.152 with a p-value of 0.002 confirms **the direct significance** of this relationship, and therefore, **H3 is accepted**. This finding contributes anew to the literature, particularly in the context of AIKU, highlighting the importance of PEX in predicting BIN. The difference with previous research may lie in the specificity of AIKU application, where development and marketing efforts should focus on improving PEX through better features and superior user experience, such as accurate air quality measurements and user-friendly features.

The complex dynamics of factors influencing BI regarding AIKU application, with two hypotheses, **H4** about EE and **H5** about SIN, show indirect non-significant results. Path coefficients of H4 at 0.059 and H5 at 0.028, while indicating the expected direction of the relationship, have low T-statistics and high p-values of 1.135 and 0.256 for H4, and 0.615 and 0.538 for H5, respectively, confirming that these relationships **lack statistical significance**. Therefore, **H4 and H5 are rejected**. In the context of previous research, these non-significant results may indicate differences with previous findings that might emphasize a greater role of effort expectations and norms in the use of similar applications. This opens the door for further exploration of factors that might be more dominant in AIKU use. Although H4 and H5 results are not significant, it does not diminish the relevance of AIKU application in the context of technology adoption. Instead, this finding can be considered a call to continue developing the application to better align with user expectations and create positive sensations.

Highlighting the central role played by the **PV** factor in driving BIN towards the AIKU application, H6 shows that the path coefficient is 0.223. The high T-statistics value of 4.309 with a p-value of 0 indicates that this relationship is significant directly. Therefore, **H6 is accepted**. This finding provides new insights into the technology adoption literature, demonstrating that economic factors such as price value can be a strong driver for users to adopt AIKU. In the context of previous research, this significant result may indicate that previous research has not fully recognized the impact of price value in the AIKU application context. Users are more willing to adopt technology when they perceive that the value they receive is commensurate with the costs incurred. Therefore, AIKU developers can leverage this finding to adjust their pricing strategies, create clearer value for users, and enhance their trust in the application.

By opening new horizons in understanding the factors influencing the adoption of the AIKU application, **H7** highlights the important role of HT as a mediator between PR and user BIN towards the artificial intelligence-based air quality system (AIKU). A significant path coefficient of 0.787 indicates that HT plays a crucial role in mitigating the impact of perceived risks by users, indicating that the higher the perceived risks by users, the higher their tendency to form positive habits related to AIKU usage. Statistical support from T-statistics of 3.412 with a p-value of 0 confirms the direct significance of this relationship, and therefore, **H7 is accepted**. This result not only reaffirms the mediating role of habit in facing risks but also provides valuable contributions to our understanding of how users respond to risks in the context of health technology. This finding not only provides deeper insights into the interaction between risk factors and habits but also illustrates that the formation of positive habits can be an effective strategy in increasing AIKU adoption. Positive habits can be an effective strategy to strengthen user confidence in AIKU. Through the development of features and interactions that stimulate the formation of positive habits, developers can create a more satisfying and reliable user experience. This factor is highly relevant in addressing the challenges and uncertainties related to risks that often become barriers to technology adoption.

Consistent with these findings, **H8** states that Behavioral Intention (BIN) positively and significantly influences User Behavior (UB) directly in using AIKU. With a positive path coefficient of 0.415, this result confirms that the higher the behavioral intention of the user, the higher their tendency to engage in user behavior related to AIKU. The high T-statistics value of 6.381 with a p-value of 0 indicates that this relationship is statistically significant. Therefore, **H8 is accepted**. This suggests that, to achieve sustainable technology adoption, it is important to build and strengthen positive user intentions, which, in turn, will motivate actual actions in using the application.

4.5. Theoritical Contributions

This research makes a substantial theoretical contribution by integrating the UTAUT2 theoretical framework with the concept of habit (HT), exploring its influence on the adoption and sustainable use of the AIKU application for air quality monitoring. The structured research design with a quantitative approach provides a systematic foundation for data collection, analysis, and presentation of findings. The decision to expand the UTAUT2 model with the habit variable (HT) offers a more holistic understanding of the factors influencing user behavioral intentions regarding AIKU. The study specifically focuses on the AIKU context in air quality monitoring, presenting contextual and relevant theoretical insights. The use of online survey methods was chosen for practical considerations, providing advantages in reaching a broader and more efficient respondent base.

Data analysis using SmartPLS 4.0 with the PLS-SEM technique demonstrates a sophisticated and reliable approach, laying a strong foundation for research findings. The research findings significantly identify performance expectation (PEX), habit (HT), perceived value (PV), and behavioral intention (BIN) as key factors influencing user behavior (UB). These findings can serve as a foundation for more contextual and relevant AIKU development strategies.

This research provides in-depth understanding of the crucial role of habit (HT) in shaping the intentions and behaviors of AIKU users. The implications include the potential to cultivate positive habits as a strategy to enhance adoption and sustainable use. Furthermore, the study contributes to technology acceptance literature by highlighting previously less-recognized variables, such as habit, enriching and expanding the literature's perspectives. The findings also offer valuable insights in addressing risks and challenges in the context of health technology, providing potential solutions for developers and practitioners to overcome technology adoption barriers.

4.6. Managerial Implications

This study provides substantial theoretical contributions by integrating the UTAUT2 theoretical framework with the concept of habit (HT), exploring its influence on the adoption and sustainable use of the AIKU application for monitoring air quality. The structured research design with a quantitative approach provides a systematic foundation for data collection, analysis, and presentation of findings. The decision to expand the UTAUT2 model with the HT variable offers a more holistic understanding of the factors influencing user behavioral intentions in adopting AIKU. The study specifically focuses on the AIKU context in air quality monitoring, presenting contextual and relevant theoretical insights. The use of an online survey method was chosen for practical considerations, providing advantages in reaching a broader and more efficient respondent base.

Data analysis using SmartPLS 4.0 with PLS-SEM technique demonstrates a sophisticated and reliable approach, establishing a strong basis for research findings. The significant research findings identify PEX, HT, and PV as key factors influencing user behavior (UB) and BIN. These findings can serve as a foundation for more contextual and relevant AIKU development strategies.

This study provides in-depth understanding of the crucial role of HT in shaping the intentions and behaviors of AIKU users. The implications include the potential to form positive habits as a strategy to enhance adoption and sustainable use. Moreover, the research contributes to technology acceptance literature by highlighting previously less-acknowledged variables, such as habit, enriching and expanding the literature's perspective. The findings also offer valuable insights in addressing risks and challenges in the context of health technology, providing potential solutions for developers and practitioners to overcome technology adoption barriers. This concludes the theoretical contributions and proceeds with managerial implications.

4.6.1. Research Implications

The findings have significant implications that reinforce the urgency of building and maintaining the adoption and use of the AIKU application. Firstly, it is crucial to emphasize that enhancing user performance expectations (PEX) towards AIKU becomes a key focus in development and marketing strategies. Certainly, these findings can be achieved by implementing strategies to enhance application features and provide a superior user experience. Furthermore, the implications highlight the crucial role of shaping positive user habits (HT) as the key to strengthening the adoption of AIKU technology. Strategies that developers can apply may involve designing features that support the formation of positive habits, increase adoption rates, and extend system usage. Additionally, the research results indicate a focus on enhancing user trust, which should be implemented through the development of features that improve the security, reliability, and quality of AIKU services. Other strategies should be considered, taking into account other factors that may influence user intentions, apart from Effort Expectancy (EE) and Social Influence (SIN). Finally, the implications suggest that developers can adapt pricing strategies and explore more flexible business models to enhance the application's attractiveness. Improving performance and adding features perceived as equivalent to the price value can be strategic steps to increase long-term AIKU adoption. By leveraging these findings, developers can design strategies more focused on forming positive habits and providing a consistent user experience, leading to increased long-term adoption of AIKU.

4.6.2. User & AIKU Developer Implications

The implications of this research show that a profound understanding of users and their needs is key to successful development. The improvement of user performance expectations (PEX) indicates the need to focus on developing features that not only enhance application functionality but also improve the overall user experience. Developers should prioritize innovations that can provide significant added value to users, forming a strong appeal for long-term adoption and use. Furthermore, the aspect of user trust becomes a primary foundation in AIKU development. Enhancing security features, reliability, and service quality are crucial steps to strengthen user trust. Clear and transparent information about data security and user privacy will be decisive factors in building trust. Additionally, understanding the factors influencing user intentions, beyond Effort Expectancy (EE) and Social Influence (SIN), emphasizes the need for developers to understand more complex psychological dynamics to design truly holistic strategies. Finally, the smart adaptation of pricing strategies and exploration of flexible business models becomes a crucial step in enhancing AIKU's appeal. Users are more likely to adopt the application if they perceive that the value provided is commensurate with the costs incurred. By considering user needs and preferences, as well as providing appropriate pricing offers, developers can ensure that AIKU remains relevant and sought-after in the long run.

5. CONCLUSION

In the context of developing AI technology based on air quality monitoring in educational environments, the background, which is reinforced by previous research, emphasizes the importance of maintaining sustainable use for the health and comfort of students and teaching staff. In response to this need, this research aims to fill the gap in the literature by investigating the role of habit in maintaining the adoption and continued use of AIKU technology in educational settings. This research method is a quantitative approach using the UTAUT2 theoretical framework to test Habit and the sustainable use of AIKU as an air quality monitoring system. In the process, data is obtained through an online survey that includes variables in the expanded UTAUT2 model. The choice to use the UTAUT2 model as a theoretical framework is based on its superiority in explaining technology acceptance, over the long-existing TAM model and the UTAUT model which complements TAM. Data analysis uses partial least squares structural equation modeling (PLS-SEM) techniques to test research hypotheses and identify relationships between variables. By using smartPLS 4.0 and a series of analysis stages involving Model Measurement, Validity Testing, Reliability Testing, and Structural Model Testing, this research achieved significant results.

The contribution made to this research is an emphasis on Habit's role in the use of AIKU technology, which provides valuable insight into the development and promotion of AIKU in Indonesia. The results of hypothesis testing are valuable findings, where of the 8 hypotheses presented, 6 hypotheses were declared accepted, H1, H2, H3, H6, H7, & H8. The findings obtained are the variable H $\rightarrow$ BIN with an Original sample value of 0.473, t-Value 8.317, p-Valeu = 0, meaning that Habit has a significant positive influence on Behavior Intention and the H & BIN variables have a significant positive influence on the UB variable, this result is very This is different from previous research where Habit has a negative influence on Intention to Use and Perceived Usability. Another finding is that PEX, PV have a significant positive influence on the BIN variable. Meanwhile, the other 2 hypotheses were declared rejected because the results obtained showed values exceeding the predetermined threshold, both the original sample value, t-statistic, and p-Value. The mediating variables Gender and Experience were also examined to investigate whether they function as mediating factors that enhance the relationship between the variables and Long-Term Adoption (UB).

Although this research has provided valuable insight into the influence of Habit factors on intention and behavior of using the AIKU air quality system, we realize there are still several limitations to this research.

1. This research focused on one AIKU air quality system, meaning the results may not be fully applicable to similar systems.

2. The data in this study was obtained through survey methods, which can be susceptible to user response bias.

3. The focus of this research is on individual factors without considering contextual factors that may influence usage behavior.

For future research, the researcher suggests strategies and innovations to address the current limitations, ensuring the success of similar studies and providing a deeper, more holistic understanding of the acceptance and usage of air quality technology in various contexts:

1. Expand the scope of research by considering various air quality systems. This can be achieved through the integration of sensor technology and the Internet of Things (IoT) to enhance user understanding and interaction with air quality systems.

2. Utilize diverse data collection methods, such as in-depth interviews or observations, to gain a more comprehensive understanding of user behavior.

3. Explore contextual factors influencing the use of these systems, including government regulations.

4. Enhance security and privacy aspects to instill user confidence regarding the collection and processing of their data.

5. Investigate the influence of cultural and social factors on the adoption of air quality technology to design solutions more aligned with local values and norms.

6. DECLARATIONS

6.1. Author Contributions

Conceptualization: D.M, U.R., I.S., Q.A., and A.W.; Methodology: I.S; Validation: D.M. and I.S.; Formal Analysis: U.R. and A.W.; Investigation: A.W.; Resources: Q.A.; Data Curation: D.M.; Writing Original Draft Preparation: Q.A and H.K.; Writing Review and Editing: Q.A. and U.R.; Visualization: A.W.; All authors, D.M, U.R., I.S., Q.A., and A.W., have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

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

6.3. Funding

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

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1] D. Indriyani and L. Meria, "Influence of work environment and work characteristics on turnover intention system with mediation role of work engagement," *International Journal of Cyber and IT Service Management*, vol. 2, no. 2, pp. 127–138, 2022.

[2] A. Ace and A. Rio, "8remote sensor network application for monitoring system and air quality classification," *IAIC Transactions on Sustainable Digital Innovation (ITSDI) The 3rd Edition Vol. 2 No. 1 October 2020*, p. 32, 2021.

[3] F. P. Oganda, M. H. R. Chakim, W. E. Septian, E. D. Astuti *et al.*, "User involvement on air quality in incubation rooms in banten-indonesia," *ADI Journal on Recent Innovation*, vol. 5, no. 1, pp. 86–92, 2023.

[4] R. E. Caraka, Y. Lee, R. Kurniawan, R. Herliansyah, P. A. Kaban, B. I. Nasution, P. U. Gio, R. C. Chen, T. Toharudin, and B. Pardamean, "Impact of covid-19 large scale restriction on environment and economy in indonesia," *Global Journal of Environmental Science and Management*, vol. 6, pp. 65–84, 2020.

[5] A. Goshua, C. A. Akdis, and K. C. Nadeau, "World health organization global air quality guideline recommendations: Executive summary," *Allergy*, vol. 77, pp. 1955–1960, 2022.

[6] Y. Y. R. Rachmawati, Y. P. A. Sanjaya, and S. Edilia, "Web-based temperature, oxygen saturation, and heart rate monitoring system," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 4, no. 1, pp. 38–45, 2022.

[7] A. Phosri, K. Ueda, V. L. H. Phung, B. Tawatsupa, A. Honda, and H. Takano, "Effects of ambient air pollution on daily hospital admissions for respiratory and cardiovascular diseases in bangkok, thailand," *Science of the total environment*, vol. 651, pp. 1144–1153, 2019.

[8] E. Von Schneidemesser, K. Steinmar, E. C. Weatherhead, B. Bonn, H. Gerwig, and J. Quedenau, "Air pollution at human scales in an urban environment: Impact of local environment and vehicles on particle number concentrations," *Science of the Total Environment*, vol. 688, pp. 691–700, 2019.

[9] M. Takahashi, Z. Feng, T. A. Mikhailova, O. V. Kalugina, O. V. Shergina, L. V. Afanasieva, R. K. J. Heng, N. M. A. Majid, and H. Sase, "Air pollution monitoring and tree and forest decline in east asia: A review," *Science of the Total Environment*, vol. 742, p. 140288, 2020.

[10] A. K. S. Ong, Y. T. Prasetyo, P. Kusonwattana, K. A. Mariñas, N. Yuduang, T. Chuenyindee, K. P. E. Robas, S. F. Persada, and R. Nadlifatin, "Determining factors affecting the perceived usability of air pollution detection mobile application "airvisual" in thailand: A structural equation model forest classifier approach," *Heliyon*, vol. 8, 2022.

[11] Q. Aini, U. Rahardja, D. Manongga, I. Sembiring, M. Hardini, and H. Agustian, "Iot-based indoor air quality using esp32," in *2022 IEEE Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2022, pp. 1–5.

[12] A. W. Kusuma, Y. Jumaryadi, A. Fitriani *et al.*, "Examining the joint effects of air quality, socioeconomic factors on indonesian health," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 5, no. 2sp, pp. 186–195, 2023.

[13] H. Fatemidokht, M. K. Rafsanjani, B. B. Gupta, and C.-H. Hsu, "Efficient and secure routing protocol based on artificial intelligence algorithms with uav-assisted for vehicular ad hoc networks in intelligent transportation systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, pp. 4757–4769, 2021.

[14] U. Rahardja, Q. Aini, D. Manongga, I. Sembiring, and I. D. Girinzio, "Implementation of tensor flow in air quality monitoring based on artificial intelligence," *International Journal of Artificial Intelligence Research*, vol. 6, no. 1, 2023.

[15] H. Hashim, "Application of technology in the digital era education," *International Journal of Research in Counseling and Education*, vol. 1, p. 1, 2018.

[16] L. Wang, G. Xie, and C. Chen, "Price competition and blockchain technology adoption strategies of agents on the digital platform," *Frontiers in Psychology*, vol. 13, p. 984928, 2022.

[17] B. Bhima, A. R. A. Zahra, T. Nurtino, and M. Z. Firli, "Enhancing organizational efficiency through the integration of artificial intelligence in management information systems," *APTISI Transactions on Management*, vol. 7, no. 3, pp. 282–289, 2023.

[18] D. P. Lazirkha *et al.*, "The impact of artificial intelligence in smart city air purifier systems," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 4, no. 2, pp. 205–214, 2022.

[19] U. Rahardja, Q. Aini, D. Manongga, I. Sembiring, and Y. P. A. Sanjaya, "Enhancing machine learning with low-cost p m2. 5 air quality sensor calibration using image processing," *APTISI Transactions on Management*, vol. 7, no. 3, pp. 201–209, 2023.

[20] P. Bhalgat, S. Bhoite, and S. Pitare, "Air quality prediction using machine learning algorithms," *International Journal of Computer Applications Technology and Research*, vol. 8, pp. 367–370, 2019.

[21] K. D. Nusandari, R. Widayanti, Y. F. Achmad, A. H. Azizah, N. A. Santoso *et al.*, "Analisis kesuksesan pengguna tangerang live menggunakan information system success model (issm)," *Jurnal MENTARI: Manajemen, Pendidikan dan Teknologi Informasi*, vol. 1, no. 1, pp. 77–88, 2022.

[22] A. Samad, S. Garuda, U. Vogt, and B. Yang, "Air pollution prediction using machine learning techniques–an approach to replace existing monitoring stations with virtual monitoring stations," *Atmospheric Environment*, vol. 310, p. 119987, 2023.

[23] J. Manuputty, I. Sembiring, and K. D. Hartomo, "Analysis of community satisfaction with the service systems in civil registry service office, south buru regency using the tam (technology acceptance model) method," *Khazanah Informatika: Jurnal Ilmu Komputer dan Informatika*, vol. 9, no. 2, pp. 169–178, 2023.

[24] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS quarterly*, pp. 319–340, 1989.

[25] B. Al Aufa, I. S. Renindra, J. S. Putri, and M. I. Nurmansyah, “An application of the unified theory of acceptance and use of technology (utaut) model for understanding patient perceptions on using hospital mobile application,” *Enfermería Clínica*, vol. 30, pp. 110–113, 2020.

[26] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of information technology: Toward a unified view,” *MIS quarterly*, pp. 425–478, 2003.

[27] V. Venkatesh, J. Y. Thong, and X. Xu, “Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology,” *MIS quarterly*, pp. 157–178, 2012.

[28] K. Tamilmani, N. P. Rana, S. F. Wamba, and R. Dwivedi, “The extended unified theory of acceptance and use of technology (utaut2): A systematic literature review and theory evaluation,” *International Journal of Information Management*, vol. 57, p. 102269, 2021.

[29] N. K. A. Dwijendra, M. Zaidi, I. G. N. K. Arsana, S. E. Izzat, A. T. Jalil, M.-H. Lin, U. Rahardja, I. Muda, A. H. Iswanto, and S. Aravindhan, “A multi-objective optimization approach of smart autonomous electrical grid with active consumers and hydrogen storage system,” *Environmental and Climate Technologies*, vol. 26, no. 1, pp. 1067–1079, 2022.

[30] S.-C. Chen, S.-H. Li, S.-C. Liu, D. C. Yen, and A. Ruangkanjanases, “Assessing determinants of continuance intention towards personal cloud services: Extending utaut2 with technology readiness,” *Symmetry*, vol. 13, no. 3, p. 467, 2021.

[31] I. Manisalidis, E. Stavropoulou, A. Stavropoulos, and E. Bezirtzoglou, “Environmental and health impacts of air pollution: a review,” *Frontiers in public health*, vol. 8, p. 505570, 2020.

[32] J. Zhu, C. Lu, and Z. Wei, “Perception of air pollution and the evaluation of local governments’ environmental governance: An empirical study on china,” *Atmosphere*, vol. 14, no. 2, p. 212, 2023.

[33] M. Hardini, R. A. Sunarjo, M. Asfi, M. H. R. Chakim, and Y. P. A. Sanjaya, “Predicting air quality index using ensemble machine learning,” *ADI Journal on Recent Innovation*, vol. 5, no. 1Sp, pp. 78–86, 2023.

[34] V. V. Febiandini and M. S. Sony, “Analysis of public administration challenges in the development of artificial intelligence industry 4.0,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 4, no. 2, pp. 164–168, 2023.

[35] S. Madhav, A. Ahamad, A. K. Singh, J. Kushawaha, J. S. Chauhan, S. Sharma, and P. Singh, “Water pollutants: sources and impact on the environment and human health,” *Sensors in water pollutants monitoring: Role of material*, pp. 43–62, 2020.

[36] E. Grigorieva and A. Lukyanets, “Combined effect of hot weather and outdoor air pollution on respiratory health: Literature review,” *Atmosphere*, vol. 12, no. 6, p. 790, 2021.

[37] L. Aliyah, C. Lukita, G. Pangilinan, M. Chakim, and D. Saputra, “Examining the impact of artificial intelligence and internet of things on smart tourism destinations: A comprehensive study.” *Aptisi Transactions on Technopreneurship*, vol. 5, pp. 135–145, 2023.

[38] M. C. Saputra and E. Andajani, “Analysis of factors influencing intention to adopt battery electric vehicle in indonesia,” *ADI Journal on Recent Innovation*, vol. 5, no. 2, pp. 100–109, 2024.

[39] D. Dias and O. Tchepel, “Spatial and temporal dynamics in air pollution exposure assessment,” *International journal of environmental research and public health*, vol. 15, no. 3, p. 558, 2018.

[40] D. A. Vallero, *Air pollution calculations: Quantifying pollutant formation, transport, transformation, fate and risks*. Elsevier, 2023.

[41] E. Sediyono, Z. A. Hasibuan, I. Setyawan, E. P. Harahap, and A. Darmawan, “Analisa sistematis manajemen pengetahuan digital aplikasi berbasis kecerdasan buatan di universitas,” *ADI Bisnis Digital Interdisiplin Jurnal*, vol. 3, no. 2, pp. 97–109, 2022.

[42] T. Hariguna, R. Waluyo *et al.*, "Sosialisasi etika penggunaan media sosial untuk mencegah bullying pada siswa mts ushriyyah purbalingga," *ADI Pengabdian Kepada Masyarakat*, vol. 3, no. 2, pp. 107–113, 2023.

[43] M. F. Fazri, L. B. Kusuma, R. B. Rahmawan, H. N. Fauji, and C. Camille, "Implementing artificial intelligence to reduce marine ecosystem pollution," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 4, no. 2, pp. 101–108, 2023.

[44] A. Williams, R. Widayanti, T. Maryanti, and D. Julianingsih, "Effort to win the competition in digital business payment modeling," *Startupreneur Business Digital (SABDA Journal)*, vol. 1, no. 1, pp. 83–95, 2022.

[45] A. Yuriev, M. Dahmen, P. Paillé, O. Boiral, and L. Guillaumie, "Pro-environmental behaviors through the lens of the theory of planned behavior: A scoping review," *Resources, Conservation and Recycling*, vol. 155, p. 104660, 2020.

[46] R. Zalianty *et al.*, "Pengaruh kepemimpinan transformasional terhadap prestasi kerja dan organizational citizenship behavior melalui corporate social responsibility: indonesia," *ADI Bisnis Digital Interdisiplin Jurnal*, vol. 4, no. 1, pp. 27–34, 2023.

[47] I. Handayani, D. Apriani, M. Mulyati, N. A. Yusuf, and A. R. A. Zahra, "A survey on user experience of blockchain transactions: Security and adaptability issues," *Blockchain Frontier Technology*, vol. 3, no. 1, pp. 80–88, 2023.

[48] M. Merhi, K. Hone, and A. Tarhini, "A cross-cultural study of the intention to use mobile banking between lebanese and british consumers: Extending utaut2 with security, privacy and trust," *Technology in Society*, vol. 59, p. 101151, 2019.

[49] J. Kim, Y. Chang, A. Y. L. Chong, and M.-C. Park, "Do perceived use contexts influence usage behavior? an instrument development of perceived use context," *Information & Management*, vol. 56, no. 7, p. 103155, 2019.

[50] K. Tamilmani, N. P. Rana, and Y. K. Dwivedi, "Use of 'habit'is not a habit in understanding individual technology adoption: a review of utaut2 based empirical studies," in *Smart Working, Living and Organising: IFIP WG 8.6 International Conference on Transfer and Diffusion of IT, TDIT 2018, Portsmouth, UK, June 25, 2018, Proceedings*. Springer, 2019, pp. 277–294.

[51] F.-H. Huang, "Influence of environmental information on users' purchase intentions for electric two-wheelers," in *Intelligent Human Systems Integration 2021: Proceedings of the 4th International Conference on Intelligent Human Systems Integration (IHSI 2021): Integrating People and Intelligent Systems, February 22-24, 2021, Palermo, Italy*. Springer, 2021, pp. 447–453.

[52] B. A. I. Putri, F. Atha, F. Rizka, R. Amalia, and S. Husna, "Factors affecting e-scooter sharing purchase intention: an analysis using unified theory of acceptance and use of technology 2 (utaut2)," *International Journal of Creative Business and Management*, vol. 1, no. 2, pp. 58–73, 2021.

[53] I. Gunawan, A. A. N. P. Redi, A. A. Santosa, M. F. N. Maghfiroh, A. H. Pandyaswargo, and A. C. Kurniawan, "Determinants of customer intentions to use electric vehicle in indonesia: An integrated model analysis," *Sustainability*, vol. 14, no. 4, p. 1972, 2022.

[54] P. Palos-Sanchez and J. R. Saura, "The effect of internet searches on afforestation: The case of a green search engine," *Forests*, vol. 9, no. 2, p. 51, 2018.

[55] V. Singh, T. Singh, E. Higueras-Castillo, and F. J. Liebana-Cabanillas, "Sustainable road transportation adoption research: A meta and weight analysis, and moderation analysis," *Journal of Cleaner Production*, vol. 392, p. 136276, 2023.

[56] F. Sutisna, T. Handra, and Y. P. Jap, "The influence of social media marketing on purchase impulses with brand attentiveness as a mediating variable on umkm x," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 5, no. 2, pp. 136–144, 2023.

[57] V. Venkatesh, F. D. Davis, and Y. Zhu, "Competing roles of intention and habit in predicting behavior: A comprehensive literature review, synthesis, and longitudinal field study," *International Journal of Information Management*, vol. 71, p. 102644, 2023.

[58] K. Nikolopoulou, V. Gialamas, and K. Lavidas, "Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet," *Computers and Education Open*, vol. 2, p. 100041, 2021.

[59] M. Omar, S. Ismail, and A. Kasim, "The influence of mobile technology adoption among secondary school teachers using the utaut 2 model," *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 8, no. 4, pp. 3827–3831, 2019.

[60] S. Watini, H. Latifah, D. Rudianto, and N. A. Santoso, "Adaptation of digital marketing of coffee msme products to digital transformation in the era of the covid-19 pandemic," *Startupreneur Business Digital (SABDA Journal)*, vol. 1, no. 1, pp. 19–33, 2022.

[61] A. Felix and G. D. Rembulan, "Analysis of key factors for improved customer experience, engagement, and loyalty in the e-commerce industry in indonesia," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 5, no. 2sp, pp. 196–208, 2023.

[62] U. Rahardja, I. D. Hapsari, P. H. Putra, and A. N. Hidayanto, "Technological readiness and its impact on mobile payment usage: A case study of go-pay," *Cogent Engineering*, vol. 10, no. 1, p. 2171566, 2023.

[63] S. Y. Putri, L. Meria *et al.*, "Pengaruh persepsi nilai dan kepercayaan terhadap keputusan pembelian yang di mediasi oleh minat beli," *Technomedia Journal*, vol. 8, no. 1 Special Issues, pp. 92–107, 2023.

[64] D. P. Restuputri, F. B. Refoera, and I. Masudin, "Investigating acceptance of digital asset and crypto investment applications based on the use of technology model (utaut2)," *FinTech*, vol. 2, no. 3, pp. 388–413, 2023.

[65] C.-M. Chao, "Factors determining the behavioral intention to use mobile learning: An application and extension of the utaut model," *Frontiers in psychology*, vol. 10, p. 446627, 2019.

[66] T. Mariyanti, "Development of mobile learning applications for android based on artificial intelligence," *International Transactions on Artificial Intelligence*, vol. 1, no. 2, pp. 230–235, 2023.

[67] F. Manca, A. Sivakumar, and J. W. Polak, "Capturing the effect of multiple social influence sources on the adoption of new transport technologies and services," *Journal of choice modelling*, vol. 42, p. 100344, 2022.

[68] U. Rahardja, C. T. Sigalingging, P. O. H. Putra, A. Nizar Hidayanto, and K. Phusavat, "The impact of mobile payment application design and performance attributes on consumer emotions and continuance intention," *Sage Open*, vol. 13, no. 1, p. 21582440231151919, 2023.

[69] P. K. Chopdar, N. Korfiatis, V. Sivakumar, and M. D. Lytras, "Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the unified theory of acceptance and use of technology," *Computers in Human Behavior*, vol. 86, pp. 109–128, 2018.

[70] R. Yunita, M. S. Shihab, D. Jonas, H. Haryani, and Y. A. Terah, "Analysis of the effect of servicescape and service quality on customer satisfaction at post shop coffee tofee in bogor city," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 4, no. 1, pp. 68–76, 2022.

[71] P. K. Senyo and E. L. Osabutey, "Unearthing antecedents to financial inclusion through fintech innovations," *Technovation*, vol. 98, p. 102155, 2020.

[72] A. Asmolov and A. Ledentsov, "Industry modern: A solution for sustainable business performance's technology challenges," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 4, no. 3, pp. 306–312, 2022.

[73] A. A. Alalwan, “Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse,” *International Journal of Information Management*, vol. 50, pp. 28–44, 2020.

[74] R. K. Hudiono and S. Watini, “Remote medical applications of artificial intelligence,” *International Transactions on Artificial Intelligence*, vol. 1, no. 2, pp. 182–187, 2023.

[75] S. Kapser and M. Abdelrahman, “Acceptance of autonomous delivery vehicles for last-mile delivery in germany–extending utaut2 with risk perceptions,” *Transportation Research Part C: Emerging Technologies*, vol. 111, pp. 210–225, 2020.

[76] Y. T. Prasetyo and K. O. S. Soliman, “Usability evaluation of erp systems: A comparison between sap s/4 hana & oracle cloud,” in *2021 IEEE 8th International Conference on Industrial Engineering and Applications (ICIEA)*. IEEE, 2021, pp. 120–125.