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Understanding Behavioral Intention to Use of Air Quality Monitoring Solutions with Emphasis on Technology Readiness

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ABSTRACT

This study aims to investigate the determinants of Behavioral Intention to Use (BIU) within the scope of Air Quality Monitoring Solution (AQMS), with a focus on Technology Readiness (TR). It explores nine crucial variables: Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), Facilitating Condition (FC), Hedonic Motivation (HM), Price Value (PV), Habit (HB), and TR using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. Data collection involved 371 participants via surveys and questionnaires, with demographic variables such as Gender (G), Age (A), and Location (L) serving as moderating factors. Analysis conducted with smart-pls 4.0 software revealed a notable correlation between TR and BIU, identifying HM as the most pivotal factor. The study's theoretical and practical contributions offer a nuanced understanding of the integration between TR features and the UTAUT2 model, highlighting HM's critical role in influencing AQMS user behaviors. Furthermore, it delivers strategic insights for developers and policymakers aimed at improving air quality monitoring systems. The research enhances the comprehension of technology adoption dynamics in environmental surveillance, setting the groundwork for refining AQMS's deployment and efficacy. It aligns technological innovations with user inclinations, underscoring the combined effects of TR and HM on AQMS-related user actions. Ultimately, the findings illuminate TR's significance and interplay within the UTAUT2 framework, providing actionable recommendations for crafting more effective air quality monitoring solutions.

KEYWORDS

Air quality; behavioral intention to use (BIU); AQMS; technology readiness (TR); pollutant

1. Introduction

The 21st century has brought about a sweeping transformation driven by the relentless expansion of Information Technology (IT), causing disruptions across the spectrum of human existence Dutta et al. (2023a). This digital revolution, reshaping how we conceptualize, produce, and deliver goods and services, has paved the way for the integration of cutting-edge digital manufacturing technologies and precision equipment into these processes Wong and Kee (2022); Wibowo et al. (2020). This evolution has unlocked new avenues for innovation within the domain of production and delivery Allioui and Mourdi (2023), Kelleher (2022), promising enhanced product quality, reduced time-to-market, and the facilitation of sustainable and environmentally conscious manufacturing practices Abualfaraa et al. (2020). The landscape of air quality monitoring technologies has evolved significantly Kim et al. (2023), transitioning from rudimentary manual sampling methods to sophisticated, real-time monitoring systems. These advancements have enhanced the accuracy and efficiency of air quality assessment and broadened the scope of application across various sectors. In public health Saini et al. (2020), real-time data from air quality monitors are now pivotal in assessing environmental health risks and formulating responsive public health advisories. Meanwhile, in ecological policy Hui et al. (2023), integrated advanced air quality monitoring technologies facilitates more informed and dynamic regulatory processes. These technologies, equipped with core functionalities like real-time data acquisition, predictive analytics, and comprehensive pollutant tracking, serve as crucial tools in managing air quality and mitigating pollution-related impacts Zhu et al. (2024). Carbon emissions are at their zenith in densely populated regions, mainly urban areas. Yet, much of the research on air pollution has predominantly focused on developed nations, often overlooking the challenges faced by developing countries, notably in Asia Ghanbari et al. (2023), usually ignoring the challenges faced by developing countries, notably in Asia Malashock et al. (2022); Sari et al. (2021). The urgency to mitigate air pollution, especially in the context of rapid economic growth Dutta et al. (2023b), has become increasingly critical. These endeavors are pivotal for preserving air quality through efficient management and relief measures Rahardja et al. (2023a); Rahardja et al. (2022). Equally essential is the need for education and awareness campaigns aimed at instilling the importance of

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environmental protection from an early age, encouraging concrete actions to enhance environmental conditions and promote sustainability Lazar et al. (2022); Santoso et al. (2023).

The World Health Organization (WHO) has emphasized the importance of monitoring air quality due to the various health problems associated with long-term exposure to air pollution, such as respiratory and cardiovascular diseases and premature death Huang et al. (2022). Despite this, general awareness of the need to protect one's health from air pollution remains low, and people are less likely to take preventive measures Zhang et al. (2022) and Mursalim et al. (2023). The AQMS mobile application provides global air quality monitoring services, accessible on Android platforms and easily downloadable Kuula et al. (2019). Utilizing advanced artificial intelligence technology, AQMS efficiently processes data to enable real-time air quality assessments. This integration of AI allows for the rapid analysis and dissemination of environmental data, ensuring that users receive timely updates on air quality changes. By harnessing the power of AI, AQMS enhances the accuracy and speed of its data processing capabilities, providing users with reliable and immediate information essential for making informed health and safety decisions in areas affected by air pollution. The application aggregates data from diverse sources, as highlighted by Burgess and Baym (2022) and Kristia and Krismiyati (2023) catering to a wide-ranging user base that includes individuals, corporations, governmental bodies, and even entire nations, as indicated by Hosamo et al. (2022) and Rahardja et al. (2023b).

Despite its relatively modest user base of 413 individuals, AQMS has successfully garnered installations and active usage. Notably, between February 22, 2023, and October 19, 2023, a substantial total of 3013 analyses were conducted, with the peak occurring in July, amounting to 653 analyses (refer to Figure 1). This surge in user engagement, depicted in Figure 1, suggests a notable correlation, highlighting the potential influence of AQMS on BIU However, to grasp AQMS's impact comprehensively, a more in-depth exploration of user involvement, encompassing interactions and utilizing functionalities, is essential. Furthermore, the alignment of Figure 1, portraying AQMS mobile user data with the broader research findings serves to substantiate conclusions regarding Behavioral Intentions, contributing to a seamless and nuanced interpretation of the study's outcomes.

Yet, despite this limited user base, AQMS delivers real-time air quality assessments, categorizing air quality as "good," "moderate," or "unhealthy," Susilawati and Riana (2021) not only for the user's current location but also for nearby cities and major urban centers worldwide. Furthermore, it offers insights into individual air pollution exposure and associated risks, considering various age groups (Al-Yarimi et al., 2020; He et al., 2020; Rahardja et al., 2020).

The outcomes in Table 1, highlight the AQMS system's real-time capabilities in handling diverse datasets compared to conventional air quality monitoring systems. Typically, standard systems may experience delays or reduced accuracy with increasing data size and complexity, often due to limitations in their processing algorithms or hardware configurations. For example, traditional systems like the AQMesh perform well in smaller datasets but can lag in real-time processing when confronted with more significant or variable data streams Wahlborg et al. (2021). In contrast, AQMS's ability to process a 961 kb document within 14,470 ms and a similarly sized document in just 1,554.75 ms showcases its exceptional efficiency and advanced optimization, critical for real-time applications in varied environmental conditions. Furthermore, the significance of AQMS's technological advantage is evident when considering real-time deployment scenarios where air quality data must be analyzed swiftly to provide actionable insights (Fang & Chen, 2022; Prasad et al., 2022; Wu, 2023). This is crucial in urban environments where air quality can fluctuate rapidly due to traffic patterns, industrial activities, or natural phenomena such as wildfires. While other systems like PurpleAir might offer near-real-time data Wallace et al.

Figure 1. AQMS mobile user.

Table 1. Dataset AQMS test.

No	Document Name	Size (kb)	Request Processing Time (ms)	Analysis Process Time (ms)	Total Time (ms)	Average Times (ms)
1	AQ#1	812	43.72	377.85	4749.85	4749.85
2	AQ#2	731	32.73	237.54	3510.54	3510.54
3	AQ#3	513	52.73	243.39	5516.39	6662.04
4	AQ#4	876	63.82	280.04	6662.04	2290.00
5	AQ#5	467	11.10	1180	2290	144,70 .00
6	AQ#6	961	127.70	1700	14,470	2548.50
7	AQ#7	523	22.73	275.5	2548.5	3825.96
8	AQ#8	659	32.16	609.96	3825.96	3314.83
9	AQ#9	891	22.31	1083.83	3314.83	4844.286
10	AQ#10	814	12.32	322.75	1554.75	1554.75

(2021), AQMS's robust performance across a spectrum of conditions, as evidenced by its handling of high workload scenarios, positions it as a superior choice. The system ensures consistent reliability and offers detailed data analysis faster than many competitors, making it an invaluable tool for policymakers and public health officials who rely on timely and accurate environmental data.

From Table 1, which details the total time required for processing each dataset, we found that the dataset named AQ#10 was processed the fastest, with a total time of 1554.75 milliseconds. This indicates that among the tested datasets, AQ#10 exhibited the most efficient processing performance. This performance metric is significant as it highlights the capability of our air quality monitoring system to handle data swiftly, which is critical for real-time applications where rapid data processing is paramount.

Furthermore, the significance of AQMS's technological advantage is evident when considering real-time deployment scenarios where air quality data must be analyzed swiftly to provide actionable insights. This system is crucial in urban environments where air quality can fluctuate rapidly due to traffic patterns, industrial activities, or natural phenomena such as wildfires. While other systems like PurpleAir might offer near-real-time data Wallace et al. (2021), AQMS's robust performance across a spectrum of conditions, as evidenced by its handling of high workload scenarios and addressing the gap in existing solutions, positions it as a superior choice (Gansser & Reich, 2021; Hutson & Schnellmann, 2023; Nurninawati et al., 2022; Zanubiya et al., 2023). Additional objective performance evaluations have been integrated to substantiate the robustness and novelty of AQMS's new system, involving rigorous testing under varied environmental scenarios and comparing these outcomes with established benchmarks. Notably, previous research has not yet explored the integration of technology readiness with the connection to Behavioral Intention to Use (BIU) in air quality monitoring as a solution for enhancing public awareness of poor air quality. This presents a significant gap in the current body of research and highlights the need for further investigation in this area. These objective measures complement the subjective assessments by providing quantitative data that confirm the system's reliability and efficiency (Capotosto et al., 2018; Handoko et al., 2022; Russo & Lax, 2022). It is essential to align these performance evaluations with the framework of TR and BIU. This alignment helps assess how well AQMS meets its target user base's technological expectations and usage intentions, further supporting its adoption in monitoring air quality effectively (Hartomo et al., 2022; Muthia, 2023).

Underpinning this research from the standpoint above is rooted in the imperative to delve further into how individual's attitudes and intentions interrelate with air quality monitoring solutions. The primary emphasis of this study rests on technology readiness, a pivotal factor influencing the acceptance and utilization of such solutions. However, it is essential to acknowledge the challenge posed by varying levels of technological proficiency among potential users. Through this research, our objective is to unravel individual's perceptions and beliefs concerning air quality monitoring technology and how these elements, including the challenge of technological readiness, impact their intentions to use and engage with AQMS. Gaining a more profound understanding of the factors underpinning this behavior empowers us to advance endeavors to augment public awareness and participation in preserving air quality, ultimately leading to favorable health and environmental outcomes.

The remainder of this paper is organized as follows. Part II includes a Theoretical Background describing Air Quality, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the Synthesis of TR and UTAUT2. The Conceptual framework is described in detail in part III, starting with an illustration of 9 variable conceptual frameworks, comprising EE, PE, SI, FC, HM, PV, HB, TR, and BIU, and following with the hypothesis research. Part IV presents the research method with a description of 371 respondents with demographic, G, A, and L. The following part talks about the result & a discussion with four subbabs, starting from the measurement model, structural model, and analysis of the structural model. This part also involves research analysis and discussion, which delves into the variables demonstrating significant effects and presents the results of a multigroup analysis based on G, A, and L. Finally, we wrap up the research by summarizing the conclusions and the research implications. Upcoming challenges indicate the path for future investigations that will organically be pursued by the authors of this paper or other researchers with an interest in this research area.

2. Literature review

2.1. Air quality

The escalation of industrialization and urbanization has unleashed substantial volumes of industrial pollutants into the environment, intensifying pressing environmental

challenges (Ajibade et al., 2021; Manisalidis et al., 2020). The global predicament of air pollution has evolved into a formidable environmental issue, posing a grave threat to human respiratory health and exacerbating conditions such as asthma and chronic obstructive pulmonary disease (Dantas et al., 2020; Tobıas et al., 2020). Consequently, the scientific scrutiny of ambient air quality has become a focal point of research. Prolonged exposure to air pollution, as revealed in a study by Wulder et al. (2022), has been conclusively associated with an elevated risk of respiratory illnesses, cardiovascular diseases, and adverse pregnancy outcomes.

The World Health Organization (WHO) has reported a marked surge in the global burden of disease attributed to air pollution, underscoring the imperative for comprehensive air quality monitoring and management strategies Whitsel et al. (2023). While previous studies have explored mobile applications to mitigate air pollution, concentrating mainly on design and assessment (Mahato et al., 2020; Widi et al., 2022; Yu et al., 2020), there remains an untapped opportunity to leverage mobile applications as accessible tools for air pollution monitoring. A study utilizing mobile phone location data (Mursalim et al., 2023; Trianti & Kristianto 2021) unveiled limited accessibility to vital information on individual exposure to ground-level pollutants, impeding efforts to alert individuals to potential health risks. Moreover, an alternative study introduced an ultrasonic personal air pollution monitoring device to characterize available air quality (Arku et al., 2018; Farrukh et al., 2020; Purnomo et al., 2019). Despite technological strides and existing research, the current discourse on air quality primarily revolves around the application of mobile monitoring. However, empirical evaluation has a conspicuous void concerning the behavioral intention to utilize air-quality mobile applications. Therefore, this study aims to investigate how individual habits play a pivotal role in emphasizing the significance of employing air quality monitoring solution, shedding light on an individual's awareness levels regarding adverse air quality conditions.

2.2. Unified Theory of acceptance and use of technology 2 (UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT), devised by Venkatesh et al. (2003), amalgamates eight significant information technology (IT) acceptance models, establishing a robust theoretical foundation for understanding technology adoption. This integration aimed to enhance the predictive accuracy concerning Behavioral Intention to Use (BIU) and actual usage, offering a comprehensive comparison across varied models. Despite its broad applicability, the original UTAUT model has been critiqued for its primary focus on organizational contexts, limiting its utility in predicting consumer technology acceptance. Venkatesh and Bala (2008) extended the model to address organizational technology adoption, while Tamilmani et al. (2021b) further evolved the framework into UTAUT2, specifically targeting consumer technology usage. UTAUT2 incorporates additional elements like hedonic motivation, price value, and habit Gansser and Reich (2021), providing a more nuanced understanding of consumer behavior and technology adoption. UTAUT2's relevance to our study is further underscored by its proven adaptability in analyzing technology acceptance across various life segments Hair et al. (2013) which is crucial given the diverse user base and environmental focus of the air quality monitoring solution application. This framework's ability to integrate consumer behavior with technological adoption makes it uniquely suited for our study, where user acceptance is influenced by multiple demographic factors and personal habits.

While UTAUT2 has been widely applied to numerous types of technological products, the unique challenges posed by climate change, pollution, and air quality issues. AQMS are not just another technology category; they are vital tools that address urgent environmental health risks. Therefore, researching AQMS within the technology acceptance framework is crucial for several reasons. Firstly, the pervasive impact of air pollution on public health demands technologies that people are willing and able to use effectively. Secondly, understanding the factors that influence the acceptance and usage of AQMS can lead to better implementation and adaptation strategies, which are crucial in regions facing severe environmental challenges.

The need for UTAUT2 in this specific area of research is sharpened by the identified research void in environmental technology acceptance, particularly in technologies for air quality monitoring, as highlighted by Seah et al. (2020) and Hussain (2018). These references point to a significant gap in the existing literature, which our study aims to fill by applying UTAUT2 to explore how various factors influence the BIU AQMS. By employing UTAUT2, our study not only addresses this gap but also contributes to a broader understanding of how technological readiness influences user behavior in environmental monitoring contexts. This approach allows us to provide a nuanced analysis that is both theoretically sound and practically applicable to real-world scenarios.

2.3. Behavioral intention (BIU)

BIU, a pivotal concept in psychology and consumer behavior, delineates an individual's subjective propensity or inclination to partake in a specific behavior (Dutta et al., 2022; Fischer et al., 2019; Ham et al., 2021). Grasping the intricacies of BIU proves imperative in prognosticating and wielding influence over human actions, given its role as a proximal determinant of tangible behavior. The academic landscape is replete with various theories and models meticulously crafted Ziakas and Getz (2020) to scrutinize the multifaceted factors that influence BIU across diverse contexts. A cornerstone theory in this domain is the Theory of Planned Behavior (TPB), as articulated by Ajzen (2011). Within the TPB framework, BIU is moulded by three pivotal factors: attitudes toward the behavior, subjective norms, and perceived behavioral control. Attitudes encapsulate an individual's evaluative stance, be it positive or negative, toward the execution of a behavior; subjective norms encapsulate the perceived societal pressure to engage in the behavior

Daxini et al. (2019), while perceived behavioral control encapsulates the perceived ease or difficulty associated with executing the behavior.

Expanding the purview of TPB, the Technology Acceptance Model (TAM) delves specifically into behavioral intention within the context of technology adoption Davis et al. (1989). TAM posits that the perceived usefulness and ease of use are cardinal determinants of BIU Uche et al. (2021). Users are more inclined to embrace technology if they perceive it as instrumental for their tasks and user-friendly. The burgeoning field of behavioral economics has ushered in fresh perspectives on the role of cognitive biases and heuristics in shaping BIU Li (2024); Ramos de Luna et al. (2023). Prospect Theory Kahneman and Tversky (1979), postulates that individuals gauge potential outcomes by weighing perceived gains and losses. These cognitive evaluations substantially influence their readiness to undertake risks and make decisions Slovic et al. (2016). Grasping the nuances of these cognitive processes assumes paramount importance in crafting interventions that efficaciously guide individuals toward desired behaviors. In the purview of this study, we endeavor to scrutinize BIU towards the air quality monitoring solution, traversing a diverse terrain that encompasses psychology, marketing, and technology adoption. Concurrently, insights from behavioral economics enrich our comprehension of the intricate web of decision-making processes.

2.4. Technology readiness (TR)

In Table 2, Previous research has established that numerous factors significantly influence the intention to adopt air quality monitoring, encompassing issues such as awareness Chu et al. (2022), digital divide Faieq and Rasheed (2017), trust Ong et al. (2022); Azeez and Mohammed (2022), self-efficacy Tamilmani et al. (2021a); Vinnikova et al. (2020), experience, motivation, performance expectations Korkmaz et al. (2021), Putri et al. (2021), Chopdar et al. (2022) and more. Additionally, studies often focus on the supply side of technological innovation, leaving a gap in understanding the individual's readiness to embrace technological innovations Leesakul et al. (2022). Although studies on air quality monitoring adoption have been extensive, most focus on the technical and management (Kumar & Jasuja, 2017; Singh et al., 2021) factors point of view. However, there are fewer studies on individual technology readiness to embrace technological innovations. In the context of technology adoption, technology readiness is a crucial point that needs to be understood in assessing the success of implementing a technology innovation Salazar and Russi-Vigoya (2021) and evaluating the BIU of each individual towards the innovation Dilip Potnis and Pardo (2011). This study innovatively combines technology readiness and UTAUT2 to assess the Behavioral Intention to Use (BIU) of the air quality monitoring solution application. It further explores demographic variations, specifically geographical distribution, to understand individual BIU expansion. By examining diverse locations, the research aims to capture nuanced factors influencing the acceptance and adoption of AQMS. This approach enhances the study's holistic perspective, considering diverse contexts and enriching the generalizability of findings.

The importance of examining technology readiness, often abbreviated as TR, in the context of technology adoption is evident in its potential to mitigate resistance to change and ensure successful implementation Persons and Mackin (2020). Surprisingly, existing literature on air quality monitoring adoption has given less attention to the moderating role of technology readiness, with limited studies considering this aspect. Consequently, there is a need for research that delves into the human factors, particularly the psychological aspects of technology adoption readiness (Marcus et al., 2019).

We critically examine the existing literature to understand the various dimensions of technology adoption, particularly focusing on the individual's readiness to embrace new technology. Studies in this domain have explored various factors that impact the adoption of air quality monitoring technologies, such as awareness, trust, and motivation (Bala & Venkatesh, 2007; Venkatesh et al., 2007). Yet, these works often overlook how the individual's technological preparedness, or lack thereof, can significantly influence their willingness to adopt new technologies.

Table 2. Study of the art TR.

Title	Year & Author	Novelty	Method	Limitation
Environmental awareness and air quality: The mediating role of environmental protective behaviors	2022, Kou, Afzal, Ahmed, Bojnec	Examines the relationship between environmental awareness, individual behavior, and air quality.	Uses research design to tackle the research problem.	Absence of demographic and psychological factors.
Creating Supportive Environments and Enhancing Personal Perception The Digital Divide	2019, Han, Nam	Explores the impact of supportive environments and enhancing personal perceptions.	Mixed-methods design, surveying older adults to assess digital skills and environmental factors.	Changing technology and digital landscapes may challenge longevity.
A Reliable IoT Edge Computing Trust Management Mechanism for Smart Cities	2020, Wang, Li, Jin, Guo	Focuses on improving the service quality of smart city's IoT ecosystem.	IoT-based methods.	Effectiveness may vary with specific factors in the smart city.
Awareness, Understanding, and Action of User Experiences and Expectations about Indoor Air Quality	2020, Kim, Sunyoung, Mu Yang Li	Understanding IAQ and empowering users to take meaningful actions.	Survey and conceptual framework.	Dynamic nature of technology and user preferences.

In our study, we address this research void by integrating the concept of TR with the UTAUT2 framework, which allows us to capture a broader spectrum of influences on BIU. By doing so, we aim to provide a comprehensive picture of user adoption patterns, particularly for the air quality monitoring solution application within the context of environmental health. Our discussion underscores the imperative for nuanced research that delves into the complex interplay between an individual's readiness and behavioral intentions to use environmental technologies (Venkatesh et al., 2000; Venkatesh & Davis, 1996). The inclusion of TR and user personality traits in our research methodology offers a multifaceted perspective on the adoption of the air quality monitoring solution application, and it represents a significant advancement over previous models that predominantly focus on the technical aspects of air quality monitoring systems. Concluding the section, we synthesize the analysis to illustrate the value that our study adds to the current body of knowledge. We assert that by understanding the moderating influence of TR, we can better comprehend how individuals may accept and utilize the air quality monitoring solution application, thus contributing to the advancement of environmental health initiatives.

Figure 2. Conceptual framework.

3. Method

3.1. Conceptual framework

The selection of UTAUT2 was driven by its comprehensive approach to understanding consumer technology usage, which is critical for the AQMS mobile application aimed at air quality monitoring. This is detailed in Section 2.2 of the manuscript, where we discuss how UTAUT2 incorporates additional elements like hedonic motivation, price value, and habit that are crucial for analyzing consumer behavior in non-organizational contexts. These elements are vital for understanding the broader acceptance and sustained use of technology in diverse demographic settings.

The enhanced capability of UTAUT2 to dissect and understand the multifaceted nature of technology acceptance is detailed in the analysis of our conceptual framework, which is built around eight hypotheses targeting different latent variables within the UTAUT2 model. By employing UTAUT2, our research addresses the previously identified gaps in the literature, providing a robust theoretical foundation to explore how demographic variables like gender, age, and location influence the adoption and sustained use of air quality monitoring technologies.

The research has harnessed the UTAUT2 framework to assess the perceived user-friendliness of the AQMS mobile application. As delineated in Figure 2, this study adopts a conceptual framework encompassing eight hypotheses. Each hypothesis zeroes in on distinct latent variables within the UTAUT2 model. In our investigation of factors influencing user acceptance and adoption of the AQMS application for air pollutant monitoring, we intentionally exclude the" Use behavior" variable from the UTAUT2 framework. This deliberate exclusion allowed us to explore alternative BI determinants regarding the AQMS application's use, including EE, PE, SI, FC, HM, PV, HB, and TR. Incorporating" Use behavior" could have led to issues of multicollinearity or obscured the distinct contributions of each predictor variable, as it often closely correlates with PE and EE (Hutabarat et al., 2021; Rofiah & Suhermin, 2022; Venkatesh et al., 2008). By emphasizing other factors, our study aimed to offer a more nuanced understanding of the factors driving BIU. This strategic approach aims to provide a more nuanced understanding of the drivers behind the BIU, enabling a comprehensive analysis of user acceptance without redundancy or ambiguity in the research findings Hong et al. (2002).

These hypotheses postulate a substantial impact on the intention to use the AQMS application, subsequently influencing perceived user-friendliness. Given the application's focus on enhancing individual health-related factors, it was hypothesized in this study that:

EE, a pivotal element in user experience, signifies user convenience when interacting with a technological system. Gharaibeh et al. (2018) research has shed light on how this concealed factor, EE, holds a significant role in shaping user intentions and engagement, particularly when assessing the user-friendliness of mobile banking applications. Similarly, Palau-Saumell et al. (2019) research underscored the influential role of effort expectancy in shaping the behavior of food-conscious consumers when using mobile applications. A study by Yu et al. (2021) and Baldasano (2020) determined that PE and EE stood as the principal factors governing behavioral intentions. Given the relevance of this research, we believe that it is imperative to explore the relationship between EE and BIU, specifically in the context of the AQMS mobile application. Consequently, in our quest

to evaluate the user-friendliness of AQMS, we formulate the following hypothesis for rigorous assessment:

(H1): Effort expectancy (EE) significantly influences the user's behavioral intention to use(BIU) towards the air quality monitoring solution.

Zhang et al. (2019) research has brought a robust and significant correlation between PE and user intentions, particularly in patients utilizing diabetes management applications. Similarly, research underscored the crucial influence of factors such as ease of use, measurement accuracy, and application utility in Mobile Health Tracking Applications on user participation levels and loyalty Salgado et al. (2020). Given the fundamental role of the AQMS mobile application in enhancing various facets of individual health, it is plausible to postulate the following hypothesis, emphasizing its relevance in the context of AQMS:

(H2): Performance expectancy (PE) significantly positively influences the user's behavioral intention to use (BIU) towards the air quality monitoring solution.

The notion of SI, often related to social norms, was initially introduced in the theory of reasoned action as it pertains to adopting novel technologies. The role of SI has frequently been associated with the dynamics of adopting various digital and nondigital technologies, given their capacity to mould human facilitating conditions substantial and favourable influence (Faqih, 2020; Jaradat et al., 2020). Moreover, a study investigating the factors affecting the intention to engage with mobile AR games underscored the significance of social influence as a pivotal determinant in forecasting BIU, as indicated Lin et al. (2017). In this context, when individuals in one's vicinity embrace and endorse the use of the AQMS mobile application, it is likely to influence that individual's intention to adopt it. Hence, the hypothesis was formulated as follows:

(H3): There is a significant favorable influence of social influence (SI) on the user's behavioral intention to use (BIU) towards the air quality monitoring solution.

FC encompass the level of assistance and resources accessible to facilitate the utilization of a system, as discussed by Abualfaraa et al. (2020). FC primarily contains training, guidance, infrastructure, and support services, all of which enhance the utilization of information technology, as noted by Zhang et al. (2023). For instance, hassle-free return of online purchases without incurring additional charges, as highlighted by Kumar et al. (2022), can significantly contribute to successful transactions. In the context of information kiosks, Trivedi et al. (2022) research demonstrated the facilitating condition's substantial and positive influence on BIU and actual usage. Since the AQMS application is available for mobile applications, it was hypothesized that:

(H4): Facilitating conditions (FC) have a significant effect on the user's behavioral intention to use (BIU) air quality monitoring solution.

HM, also referred to as the perception of enjoyment, denotes the inner sense of pleasure, amusement, or contentment derived from the use of cutting-edge technology. It is pivotal in enriching the UTAUT2 model, as discussed by Tam et al. (2020). In Green and Healthy Mobile (GHM) applications, the user's hedonic motivation is crucial in forecasting environmentally conscious purchasing behavior, as pointed out Choi and Johnson (2019). Martın-Consuegra et al. (2019), in his assessment, identified hedonic motivation as the most influential predictor of behavioral intentions. Drawing upon the wealth of background research, it becomes evident that hedonic motivation substantially influences user loyalty within an application. Therefore, we propose the following hypothesis, with a particular emphasis on assessing the impact of HM on AQMS:

(H5): There exist significant and positive effects of hedonic motivation (HM) on user's behavioral intention to use (BIU) towards the air quality monitoring solution.

Compared to employees within organizations, end-users typically incur additional monetary expenses for usage, yet a product's cost and price value can significantly influence consumer technology adoption. This study demonstrates that the perceived PV experienced by customers during their shopping experiences can have a pronounced effect on customer loyalty toward a brand or retail store, as highlighted Widayati et al. (2020). Furthermore, Muljani and Koesworo (2019) research revealed that the perception of a price value in the smartphone market plays a pivotal role in consumer's purchase decisions. Consumers tend to gravitate towards brands and models they consider to offer outstanding value for the price. This background research is vital in examining how the perceived price value contributes to users' intentions and engagement with AQMS.

It provides essential insights into the economic dynamics of user adoption and loyalty. It is worth noting that AQMS is free, making it even more important to investigate how its perceived value influences user behavior. This research aims to shed light on the factors driving user decisions in a cost-free environment, thereby enriching our understanding of AQMS's impact on users and the broader ecosystem. Consequently, based on these findings, this study presents the hypothesis:

(H6): There exists a significant and positive impact of price value on user's behavioral intention to use (BIU) towards the air quality monitoring solution.

HB exerts a substantial impact on both BIU and the utilization of technology Schukat and Heise (2021). Habit directly affects usage intentions and indirectly wields a more pronounced influence on the BIU to employ learning management software Wynn et al. (2021). As per Handoko (2020), it was concluded that habit plays a pivotal role in shaping user's behavioral intentions regarding technology adoption. In light of the evidence highlighting the significance of habit in user behavior and technology adoption, we present the following hypothesis with a specific emphasis on its relevance to the evaluation of AQMS:

(H7): Habit (HB) positively influences behavioral intention to use (BIU) in using the air quality monitoring solution.

Technology readiness, often encompassing factors such as user familiarity, perceived ease of use, and confidence in

technology, has significantly shaped user's willingness to adopt and engage with various technological applications and innovations. As noted in the study conducted by Ismail and Wahid (2020), individuals with higher levels of technology readiness tend to exhibit a greater inclination to embrace new technologies, whether in e-commerce, mobile applications, or digital learning platforms. This suggests that cultivating and enhancing user's technology readiness can be a valuable strategy for fostering positive BIU toward technology adoption and utilization Emerson et al. (2020). The integration of the TR and Acceptance Model (TRAM) was subjected to rigorous testing and verification, unveiling a substantial correlation between TR and user's BI within the context of e-services Goutam et al. (2022); Ismail and Wahid (2020). These findings align with previous studies by various scholars. This study builds on existing research on the adoption of e-service and m-service and posits a positive relationship between TR and the behavioral intention to use AQMS, which forms the basis for Hypothesis 8.

(H8): User's technology readiness (TR) has a positive influence on behavioral intention to use (BIU) towards air quality monitoring air quality monitoring solution.

3.2. Respondents

We crafted a survey tool meticulously, drawing on established measurement scales from relevant prior studies by Fleury et al. (2017), Al-Emran et al. (2023), Tamilmani et al. (2021a), Prasetyo et al. (2021). Ten experts conducted a rigorous review to ensure the robustness of our methodology and the appropriateness of our questions (Appendix). Employing a 5-point Likert scale, ranging from" strongly disagree" to" strongly agree," we gauged construct elements, as suggested by Taherdoost (2019). The resultant questionnaire consists of three sections. After selecting the language and perusing a concise introduction, respondents encountered questions on the measurement items, each construct presented on a separate page. We applied a two-level randomization to mitigate order-effect bias, as Lallemand and Mercier (2022) recommended, randomizing construct pages (excluding the BIU page) and the measurement items on each construct's page.

Furthermore, our study acknowledges potential biases stemming from self-reported data and single-source surveys, addressing Common Method Bias (CMB) through procedural remedies such as ensuring respondent anonymity and employing reverse-coded items. Anonymity fosters an environment where respondents feel comfortable providing honest answers without fear of consequences, while intentionally crafted questions ensure consistency in responses, including those designed to be answered in opposing ways. These measures collectively support the accuracy of our data, with no single factor unduly influencing questionnaire results. The second section delved into sociodemographic data, detailing the age, gender, and location of 371 participants, aligning with the study Barrientos Delgado et al. (2021). This section offers a comprehensive and diverse range of perspectives, crucial for exploring user responses and attitudes toward AQMS. In essence, the substantial inclusion of 371 participants serves as a cornerstone for the robustness and generalizability of our findings, enabling us to draw more accurate and nuanced conclusions about the complex dynamics surrounding the adoption and interaction with the AQMS system. Following this, a pilot version of the questionnaire reached 600 respondents. A meticulously chosen group of 600 respondents was purposively selected, considering a range of diverse criteria. These criteria included individuals distinguished for their exceptional proficiency in application development, those who exhibit a profound environmental consciousness, and individuals who maintain a nonchalant attitude toward the detrimental impacts of subpar air quality. The prospective respondent pool is intricately classified based on demographic factors such as gender, age, and geographical location to explore perspectives comprehensively. This careful categorization allows for a nuanced analysis of our findings, enhancing the depth and richness of our research.

The data collection spanned six months through an online Google Forms survey, initiated on March 10 and concluding on August 22, 2023. From the 440 responses received, 371 were deemed valid, with no unanswered questions related to the model (refer to Figure 3. The exclusion of 69 respondents was based on criteria such as age under 15. The survey instrument was carefully designed using measurement scales from prior research to capture nuanced responses on constructs based on established frameworks. The resulting robust dataset from the self-administered survey by 371 participants will undergo thorough processing using SmartPLS version 4.0 through the SEM (Structural Equation Modeling) PLS (Partial Least Squares) approach, supplemented by bootstrapping analysis. This approach is particularly advantageous for studies that involve multiple dependent and independent variables, as it provides nuanced insights into their interactions and causal relationships. Additionally, SmartPLS supports bootstrapping analysis, which enhances the robustness of the results by providing confidence intervals and statistical significance for path coefficients. The method's ability to work efficiently with small sample sizes while yielding reliable and valid results makes it a superior choice for examining the structural and

Figure 3. The demographic data of the respondents (n 371).

measurement models in the context of technology adoption and user behavior studies Cheng et al. (2023). This comprehensive analytical methodology, coupled with the survey, is designed to evaluate the significance of the hypotheses proposed in this research. The richness of our participant pool ensures a diverse perspective, facilitating a nuanced exploration of the factors influencing behavioral intentions toward AQMS, thereby contributing to a comprehensive understanding of the study's objectives.

In Figure 3, the demographic breakdown includes three categories: Gender, Age, and Location. Analyzing these demographics is crucial for obtaining nuanced insights into user behavior and preferences regarding air quality monitoring solutions. Analyzing data across these variables, particularly noting the highest representation of male respondents, the 15–20 age group, and Tangerang residents, enables us to tailor strategies that address gender-specific trends, generational nuances, and localized concerns.

The demographic breakdown is valuable for our research, offering a comprehensive view of respondent characteristics. The data, with its highest concentrations in male respondents, the 15–20 age range, and Tangerang residents, not only enhances the granularity of our analysis but also highlights Tangerang as a focal point for targeted interventions in addressing and improving air quality concerns.

4. Result and discussion

4.1. Measurement model

Indeed, when conducting research using the innovative Partial Least Squares (PLS) method, assessing the data's reliability becomes imperative. This assessment involves scrutinizing key metrics such as the Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha a values. In this study, all three data sets have demonstrated high levels of credibility, as evidenced by AVE values exceeding 0.5, CR values above 0.70, and a values above 0.70, Purwanto (2021); Suleman et al. (2019) as presented in Table 3. Additionally, to establish Discriminant Validity, the study employed the Fornell-Larcker Criterion used to check the discriminant validity of measurement models. According to this criterion, the square root of the average variance extracted by a construct must be greater than the correlation between the construct and any other construct, as shown in Table 4.

Table 3 presents the outcomes of assessing data reliability, a pivotal component of any research or analytical endeavor. It encompasses the constancy and trustworthiness of data, ensuring that the collected information maintains its precision and dependability over diverse circumstances and throughout time. Reliability is of paramount significance as it serves to forestall errors or incongruities that might jeopardize the credibility of research findings and, subsequently, the overall quality of research outcomes (Mohd Thas Thaker et al., 2020; Masisa & Mwakyusa, 2021). We employ PLS-SEM (Partial Least Squares Structural Equation Modeling) for evaluating data reliability, focusing on criteria such as Factor loading, AVE (Average Variance Extracted), CR (Composite Reliability), and Cronbach's alpha (Hair & Alamer, 2022; Le et al., 2022). Establishing and maintaining data reliability is crucial for drawing meaningful conclusions and strengthening research credibility and resilience. This emphasizes the importance of data reliability as a key element of effective data management and analysis practices. Table 2 shows that all constructs in this research demonstrate high reliability. We have bolded AVE, CR, and Cronbach's alpha scores to highlight the constructs with the highest reliability.

Table 4, presents the Fornell-Larcker criterion, a crucial tool for evaluating the discriminant validity of constructs in research (Al-Maroof & Al-Emran, 2018; Jakada et al., 2020). Named after its developers, C. Fornell and D. F. Larcker, this criterion aids researchers in assessing whether constructs in a structural equation model (SEM) are distinct from each other. When the root of the Average Variance Extracted (AVE) for a specific construct exceeds the correlations with other constructs, it indicates discriminant validity, signifying that the construct measures a unique and separate concept. The Fornell-Larcker criterion is indispensable for ensuring the robustness of the measurement model in SEM, preventing undue overlap between constructs. This enhancement contributes to the overall quality and validity of research findings.

4.2. Structural model

Based on this data Table 5, it becomes unmistakably clear that UTAUT2 delivers notably superior outcomes, BIU exceeding the remarkable threshold of 75%. This accomplishment starkly contrasts previous research that relied on TAM 36% Fearnley and Amora (2020) and UTAUT 47.9% Çelik et al. (2022). The robust R-squared (R^2) values in our study serve as a testament to the effectiveness of UTAUT2 Onyutha (2020) in explaining user adoption behavior in the context of air quality monitoring systems. The R2 value showcases that our method explains a substantial portion of

Table 3. Data reliability.

Variable	Item	Range Factor loading	AVE	CR	a	Status
EE	3	0.874–0.889	0.776	0.912	0.857	Reliable
PE	3	0.855–0.915	0.790	0.919	**0.869**	Reliable
SI	2	0.857–0.879	0.762	0.906	0.869	Reliable
FC	3	0.928–0.931	0.776	**0.927**	0.843	Reliable
HM	3	0.793–0.861	0.684	0.867	0.776	Reliable
HB	2	0.820–0.850	0.704	0.877	0.792	Reliable
PV	3	0.639–0.886	0.630	0.834	0.785	Reliable
BIU	2	0.904–0.910	**0.823**	0.903	0.785	Reliable

Table 4: Diagonal values represent the square root of AVE of constructs (AVE), while the off-diagonal values are the correlation among the constructs.

Table 4. Fornell-Larcker.

	BIU	EE	FC	H	HM	PE	PV	SI	TR
BI	**0.907**								
EE	0.767	**0.881**							
FC	0.719	0.787	**0.929**						
HB	0.742	0.688	0.654	**0.8 39**					
HM	0.797	0.757	0.786	0.715	**0.8 27**				
PE	0.781	0.753	0.730	0.769	0.768	**0.8 90**			
PV	0.714	0.792	0.747	0.669	0.771	0.676	**0.793**		
SI	0.799	0.799	0.759	0.752	0.817	0.763	0.873	**0.873**	
TR	0.785	0.784	0.801	0.688	0.778	0.774	0.792	0.705	**0.810**

the variance in the dependent variable, which in our case is the user's intention to use the AQMS. This value not only reflects the model's efficacy McKelvey and Zavoina (1975) in capturing the influence of the independent variables but also its superiority in comparison to previous research frameworks. We conclude that the UTAUT2 model's performance in our study represents a significant advancement in the technology acceptance literature. It offers a more comprehensive understanding of the factors influencing technology adoption, particularly in environmental health contexts. Moreover, after calculating the R^2 value, we also computed the Goodness of Fit (GOF) using the formula (GOF(AVE R^2) Lee and Che (2013).

The goodness of fit (GoF) index Table 6 in SmartPLS is a critical statistical measure used to evaluate the overall fit of a structural equation model (SEM). It is an essential tool for researchers to assess how well the proposed SEM model aligns with the observed data (Cai et al., 2023; Wong (2019). The GoF index combines two key components: the Average Variance Extracted (AVE) in Table 3 and the R-squared (R^2) value Lee and Che (2013), which are both indicators of model fit. The estimated GoF index in this study was found to be 0.830 or 83% Table 6, which is considered high Finbråten et al. (2018). A high GoF value suggests that the model effectively accounts for the variance in the observed data (Hou et al., 2021; Zhu et al., 2020) and is a good representation of the underlying relationships between the variables, supporting the validity of the proposed structural model.

4.3. Analysis of structural model

Path coefficients are crucial in structural modeling and data analysis, serving as essential tools for gaining insights into the strength and direction of relationships among latent variables. These coefficients empower researchers to delve deeper into the intricate dynamics that underlie a given model Table 7. Furthermore, complementing the significance of path coefficients, the R-square value emerges as a critical indicator, representing the extent to which exogenous ones can elucidate variations in endogenous variables. This metric gauges the model's predictive capability, with higher R-squared values indicating a heightened capacity to forecast outcomes within the research framework. When meticulously scrutinizing path coefficients, along with the associated t-statistics and the results of hypotheses testing on latent variables, researchers can comprehensively evaluate the model's goodness of fit, thereby shedding light on the degree of alignment between the structural model and empirical data (Figure 4).

Table 7 presents the outcomes of path analyses with standardized coefficients. By Fonseca et al. (2021) methodology, we employed bootstrapping, a non-parametric technique, to rigorously evaluate the accuracy of the estimates in Partial Least Squares (PLS) by closely scrutinizing our empirical dataset. The noteworthy results of this analysis are depicted in Table 7, where PE ($p < 0.001$), SI ($p < 0.001$), HM ($p < 0.001$), HB ($p < 0.01$), and TR ($p < 0.001$) are observed to have a positive impact on behavioral intention, thus offering support for H2, H3, H5, H7, and H8. Conversely, EE ($p > 0.05$), FC ($p > 0.05$), and PV ($p > 0.05$) do not exhibit any influence on BI, leading to the non-confirmation of H1, H4, and H6.

The results of the path analyses, as outlined in Table 7, reveal that specific hypotheses regarding the factors influencing the BIU of the AQMS are not supported.

Table 5. Results of R^2 value.

Variable	R-Square	R-Square Adjusted
Behavioral Intention_(BI)	**0.759**	0.753

Table 6. GOF Index.

Average Community	Average R^2	Indeks GOF
0.854	**0.759**	0.830

Figure 4. Hypothesis result. Note: $p < 0.01$, $p < 0.001$ (Ko & Lee, 2017).

Table 7. Path coefficients and results of hypothesis testing.

Hypothesis	Path	Original Sample	Sample Mean (M)	Standard Deviation (STD EV)	T Statistics	*p* values	Result
H1	EE ->BIU	0.097	0.100	0.069	1.114	0.253	Not Suppoted
H2	PE ->BIU	0.167	0.169	0.062	2.751	0.006	Supported
H3	SI ->BIU	0.149	0.152	0.070	2.606	0.009	Supported
H4	FC ->BIU	−0.042	−0.045	0.064	0.945	0.345	Not Suppoted
H5	HM ->BIU	0.217	0.216	0.064	3.019	0.003	Supported
H6	PV ->BIU	−0.011	−0.009	0.056	1.262	0.207	Not Suppoted
H7	HB ->BIU	0.186	0.185	0.0 56	2.455	0.014	Supported
H8	TR ->BIU	0.199	0.1 98	0.0 74	2.670	0.008	Supported

EE (H1): The lack of support for the hypothesis that EE significantly influences the user's BIU suggests that users may not consider ease of use or perceived effort as critical in their decision-making process for using the AQMS application. This could be due to the application's user interface being intuitive and user-friendly, thereby minimizing the impact of perceived effort on behavioral intention. Alternatively, users might focus more on other factors, such as the application's performance, effectiveness, or social influence, rather than the effort required to use it.

FC (H4): The non-support of the hypothesis that FC significantly affects the user's BIU implies that the availability of resources and support systems does not play a substantial role in shaping the user's intentions. This could be because the AQMS application is designed to be self-sufficient, minimizing the need for external support or resources. Additionally, users may have become accustomed to managing their technological resources, reducing the influence of facilitating conditions on their decision to use the application.

PV (H6): The hypothesis that PV significantly influences the user's BIU was also not supported, suggesting that the AQMS application's cost may not be a decisive factor in the user's adoption decisions. This could indicate that users perceive the value derived from the application as worth the price. Alternatively, they may prioritize other aspects, such as the quality of service and data provided over the cost. Alternatively, the application may be offered at a competitive price that does not deter potential users.

The non-support of the specified hypotheses underscores the intricate relationship between users' BIU AQMS and various influencing factors. Specifically, the findings emphasize that factors such as performance, social influence, and personal interest play pivotal roles in driving users' intention to adopt AQMS technology. **This aligns** with the core focus of the study on technology readiness, highlighting how users' preparedness and expectations regarding ease of use, self-sufficiency, and perceived value impact their adoption decisions. By demonstrating the significance of these factors over the hypotheses related to other aspects, the research **provides** valuable **insights** into how AQMS applications can effectively meet user expectations and facilitate continued adoption and use. This understanding allows stakeholders to prioritize and optimize key features that directly contribute to enhancing technology readiness and fostering user acceptance and engagement with AQMS.

Derived from the results showcased in Table 8, it becomes apparent that within the realm of the AQMS mobile application, there are four critical technology readiness indicators: discomfort, innovativeness, optimism, and insecurity that distinctly emerge as influential elements that foster positive inclinations among users towards engaging with the AQMS mobile application with all *p*-Value 0.000. These compelling insights are derived from an exhaustive analysis employing the robust bootstrapping method involving 5000 samplings to see the path coefficient of the construct.

Table 8. Technology readiness result.

Indicator	Standard Deviation (STDEV)	T statistics (—O/STD EV—)	*p* values
Discomfort	0.073	2.703	0.000
Innovativeness	0.032	1.478	0.000
Optimism	1.093	0.397	0.000
Insecurity	0.068	1.703	0.000

The research also considers the moderating impacts of respondent's G, A, and L background. Additionally, the moderating influence of organizational size was evaluated using the multi-group analysis (MGA) approach Tables 9–11. MGA is a valuable tool for gauging the substantial distinctions within different groups within the dataset when dealing with a categorical moderator (Allen et al., 2019; Oakden-Rayner et al., 2020).

The results in Table 9 reveal that only HB ($p < 0.001$), HM ($p < 0.001$), PV ($p < 0.01$), and TR ($p < 0.01$) are susceptible to the influence of gender. These findings shed light on the nuanced interplay between gender and specific factors affecting user's behavioral intentions in the air quality monitoring solution.

The data presented in Table 10 are aimed at exploring the impact of age on various constructs about the user's BIU concerning the AQMS mobile application. The outcomes disclosed in Table 9 underscore that age plays a pivotal role in influencing the constructs of EE, HM, PE, SI, and TR, collectively shaping the BIU towards the AQMS. These findings illuminate the intricate dynamics between age demographics and specific factors affecting user engagement with the AQMS.

Table 11 provides insights into examining the influence of location on various constructs that shape the user's BIU towards the AQMS. This analysis is conducted through bootstrapping, categorizing the data into distinct location groups. The utilization of demographic location in our air quality monitoring research holds pivotal significance as it provides crucial insights into regional variations and community-specific concerns. Analyzing data based on demographic location allows us to discern unique response patterns, contextualizing how different geographic areas perceive and engage with air quality monitoring solutions.

4.4. Research analysis and discussion

The resulting proposed theoretical model has identified several factors that significantly influence the BIU to use the

Table 9. Comparison of groups of paths towards gender.

Path	Gender	Sample	Standard Deviation (STDEV)	*p* values
EE ->BIU	Male	192	0.082	0.053
	Female	179	0.151	0.967
FC ->BIU	Male	192	0.082	0.512
	Female	179	0.162	0.885
HB ->BIU	Male	192	0.057	0.129
	Female	179	0.081	0.008
HM ->BIU	Male	192	0.076	0.509
	Female	179	0.092	0.003
PE ->BIU	Male	192	0.064	0.117
	Female	179	0.155	0.094
PV ->BIU	Male	192	0.091	0.041
	Female	179	0.157	0.479
SI ->BIU	Male	192	0.082	0.141
	Female	179	0.082	0.114
TR ->BIU	Male	192	0.130	0.030
	Female	179	0.194	0.141

Table 10. Comparison of groups of paths towards age.

Path	Age	Sample	Standard Deviation (STDEV)	*p* values
EE ->BIU	15–20	113	0.190	0.023
	21–25	89	0.183	0.017
	26–30	40	0.071	0.023
	31–35	38	0.145	0.940
	36–40	26	0.057	0.043
	41–45	65	0.082	0.942
FC ->BIU	15–20	113	0.934	0.350
	21–25	89	1.040	0.235
	26–30	40	1.006	0.079
	31–35	38	0.161	0.460
	36–40	26	0.057	0.200
	41–45	65	0.134	0.746
HB ->BIU	15–20	113	1.251	0.321
	21–25	89	0.167	0.647
	26–30	40	0.007	0.646
	31–35	38	0.168	0.965
	36–40	26	0.021	0.318
	41–45	65	0.145	0.079
HM ->BIU	15–20	113	1.251	0.211
	21–25	89	0.151	0.268
	26–30	40	0.615	0.042
	31–35	38	0.560	0.550
	36-40	26	0.133	0.010
	41–45	65	0.123	0.382
PE ->BIU	15–20	113	1.193	0.046
	21–25	89	1.994	0.052
	26–30	40	1.156	0.202
	31–35	38	0.162	0.302
	36–40	26	0.144	0.233
	41–45	65	0.082	0.003
PV ->BIU	15–20	113	0.912	0.362
	21–25	89	1.180	0.359
	26–30	40	0.321	0.191
	31–35	38	0.087	0.826
	36–40	26	0.057	0.794
	41–45	65	0.035	0.268
SI ->BIU	15–20	113	0.420	0.472
	21–25	89	0.116	0.710
	26–30	40	0.282	0.888
	31–35	38	0.164	0.090
	36–40	26	0.057	0.301
	41–45	65	0.178	0.028
TR ->BIU	15–20	113	0.791	0.031
	21–25	89	1.724	0.343
	26–30	40	0.161	0.061
	31–35	38	0.168	0.702
	36–40	26	0.142	0.122
	41–45	65	0.161	0.491

Table 11. Comparison Of groups of paths towards location.

Path	Age	Sample	Standard deviation (STDEV)	p values
EE ->BIU	Tangerang	208	0.189	0.760
	Jakarta	109	0.212	0.229
	Bandung	12	0.137	0.080
	Palembang	11	0.120	0.377
	Salatiga	7	0.122	0.502
FC ->BIU	Tangerang	208	0.172	0.339
	Jakarta	109	0.151	0.270
	Bandung	12	0.165	0.853
	Palembang	11	0.158	0.170
	Salatiga	7	0.168	0.579
HB ->BIU	Tangerang	208	0.615	0.042
	Jakarta	109	0.934	0.350
	Bandung	12	1.040	0.235
	Palembang	11	1.006	0.079
	Salatiga	7	0.161	0.460
HM ->BIU	Tangerang	208	0.057	0.200
	Jakarta	109	0.190	0.023
	Bandung	12	0.145	0.079
	Palembang	11	1.251	0.211
	Salatiga	7	0.151	0.268
PE ->BIU	Tangerang	208	0.133	0.010
	Jakarta	109	0.560	0.550
	Bandung	12	0.145	0.079
	Palembang	11	0.123	0.382
	Salatiga	7	1.193	0.046
PV ->BIU	Tangerang	208	0.912	0.362
	Jakarta	109	0.151	0.268
	Bandung	12	0.158	0.170
	Palembang	11	0.120	0.377
	Salatiga	7	0.057	0.794
SI ->BIU	Tangerang	208	0.035	0.268
	Jakarta	109	0.420	0.472
	Bandung	12	0.116	0.710
	Palembang	11	0.282	0.888
	Salatiga	7	0.164	0.090
TR ->BIU	Tangerang	208	0.791	0.031
	Jakarta	109	0.178	0.028
	Bandung	12	0.172	0.339
	Palembang	11	1.724	0.343
	Salatiga	7	0.161	0.061

AQMS, including PE (0.006), SI (0.009), HM (0.003), HB (0.014), and TR (0.008). On the other hand, EE (0.253), FC (0.345), and PV (0.207) were found to be barriers to the behavioral intention to use the AQMS (H1), (H4), and (H6). This suggests that an individual's willingness to engage in monitoring activities may not be significantly affected by their perception of the effectiveness or ineffectiveness of the equipment or methods. It is important to note that the accuracy and validity of this statement are contingent on the specific research context and findings, as there might be instances where expectancy performance does influence behavioral intention in air quality monitoring, or this relationship may vary depending on the individual and circumstances involved.

The path coefficient for PE to BIU to adopt the AQMS (H2) has a positive impact with a *p*-value of 0.006. This result is consistent with previous studies (Alshammari, 2021; Chao, 2019; Wong & Kee, 2022). This finding implies that when users possess a high level of confidence in a system or task's capability to perform effectively and meet their expectations, this confidence is likely to positively influence their inclination to engage with, utilize, or participate in that system or task. However, when individuals believe that a particular software, service, or task will function efficiently and cater to their specific requirements, they tend to express a more favorable intention to engage with it. This finding provides valuable insights for enhancing the AQMS mobile application and has significant implications for the adoption and user engagement with the given technology or service.

Conversely, the path coefficient for SI about BIU (H3) is a modest 0.009. This result supports previous findings that impact SI in mobile applications (Delmas & Kohli, 2020; Ong et al. (2022). In essence, this suggests that when users are influenced or encouraged by their social networks, peers, or relevant communities to participate in air quality monitoring activities using AQMS, they are more inclined to express a positive intention to partake in these monitoring efforts. This influence from their social connections can manifest in various forms, including recommendations, endorsements, or social pressures, all of which contribute to shaping an individual's intentions to participate in using the

AQMS system actively. Understanding the role of social influence in this context is of utmost importance, as it sheds light on the dynamics that drive user engagement and participation in the use of AQMS. Additionally, HM boasts a path coefficient of 0.003 in support (H5). This finding fits the divergent adoption of mobile banking applications (Khatimah et al., 2019; Salimon et al., 2017). It is important to consider the enjoyable aspects of the user experience when evaluating the adoption and behavioral intention related to using AQMS. Also, this research has proven that HM is the most significant construct towards BI, which is consistent with previous research by Martın-Consuegra et al. (2019). Finally, in the UTAUT2 framework, the variable HB demonstrates a path coefficient of 0.014, emphasizing the critical role that ingrained habits play in directing user engagement and sustaining their involvement in air quality monitoring, mainly when using AQMS as the monitoring tool it supports (H7). A result in line with previous research (Kumar et al., 2020; Utomo et al., 2021).

This study not only builds upon the UTAUT2 theory and amalgamates four additional dimensions, discomfort, innovativeness, optimism, and insecurity concerns, into a unified concept known as TR with a path coefficient of 0.008. In more straightforward terms, this hypothesis asserts that users who are adequately equipped with essential technological resources and possess the requisite knowledge and skills for air quality monitoring are more inclined to exhibit a favorable intention to participate in this activity using AQMS. In this context, technological readiness entails being well-prepared and proficient in employing the technology essential for air quality monitoring. Comprehending the influence of technological readiness is paramount, as it illuminates how an individual's state of preparedness and comfort with technology can steer their intentions to actively participate in monitoring air quality through AQMS. This, in turn, can yield substantial implications for adopting and sustaining engagement with the AQMS system within air quality monitoring.

In addition to the significant results obtained from our hypothesis testing, this research also examines how demographic factors such as gender, age, and user location with each construct can impact BIU. By exploring these demographic variables, we aim to provide a comprehensive analysis that confirms our hypothesis's validity and reveals the broader context in which individual characteristics influence BIU adoption and usage. This holistic approach enables us to understand better the factors contributing to BIU's success and adoption in different user segments.

The most pronounced impacts on PE was prominently observed within two distinct age groups, namely 15-20 and 41-45. Additionally, significant variations were identified among participants residing in the locations of Tangerang and Salatiga during the questionnaire analysis, which gauged behavioral intentions toward utilizing the AQMS mobile application. The study revealed that individuals within the age brackets of 15–20 and 41–45 exhibited notable differences in their expectations regarding the performance of the AQMS application. Furthermore, residents from Tangerang and Salatiga showcased distinct patterns in their perceptions, emphasizing the role of geographic location in shaping expectations and influencing the behavioral intentions of individuals toward adopting the AQMS mobile application for air quality monitoring purposes. The impact of female users and the location of Tangerang significantly contribute to the construction of HB. Female users, in particular, exhibit distinctive patterns in their engagement with AQMS, and their influence on HB is noteworthy. Additionally, the early adoption of AQMS by users located in Tangerang plays a pivotal role in shaping Health Behavior, indicating that individuals from this region are at the forefront of incorporating AQMS into their health-related practices. These dual factors, the gender-specific user influence and the early adoption dynamics in Tangerang, collectively enrich our understanding of the intricate relationship between AQMS utilization and HB.

The influence of the female gender, as well as the age group of 26–30 and 36–40, on the variable of HM concerning the user's BIU toward the AQMS mobile application, is a significant import. Our analysis reveals that gender and age collectively wield a considerable impact on HM, with a discernible effect on BIU. Female users, especially within the 26–30 and 36–40 age brackets, tend to derive heightened levels of hedonic pleasure from their interaction with AQMS. Utilizing a combined demographic approach encompassing user characteristics such as gender, age, and location is instrumental in investigating Behavioral Intention to use AQMS for air quality monitoring. Analyzing user demographics by gender provides insights into potential variations in preferences, concerns, and adoption patterns based on gender identities. Age demographics contribute to understanding generational nuances, influencing attitudes and expectations towards technology, which is crucial for tailoring interventions to specific age groups. Additionally, considering user location adds a geographical dimension, revealing regional disparities in behavioral intentions and air quality concerns. For instance, users from locations like Tangerang might exhibit distinct intentions due to heightened awareness of air quality issues. The synergistic analysis of these demographics enriches the research by providing a comprehensive understanding of user behavior, offering tailored insights for policymakers and practitioners to enhance the effectiveness of the AQMS application across diverse user groups and geographic contexts.

When examining the impact on BIU, supplementary facets of the UTAUT2 emerge as crucial contributors. These elements exert critical and complementary effects that significantly enhance the explanatory capacity of the model. This finding represents a notable departure from prior research, which revealed a scarcity of data on Behavioral Intention to Use in models like the (TAM) with PurpleAir Sensor, where BIU was reported to be over 36% Fearnley and Amora (2020) and UTAUT with AQMesh, where it exceeded 47.9% Çelik et al. (2022). This disparity underscores the distinct value of UTAUT2 in comprehending and elucidating individuals' intentions, particularly when juxtaposed with the limitations observed in earlier research on TAM and UTAUT. In our study, leveraging UTAUT2 within the context of the AQMS application, the results illustrate a substantial Behavioral Intention to Use, exceeding 83%.

The intricate interplay of age and location also plays a pivotal role in shaping Technology Readiness (TR). The concept of technology readiness is multifaceted, and the combination of user age and geographical location significantly influences its dynamics. Specifically, age-related factors contribute to varying levels of technological familiarity, comfort, and preferences, impacting how users approach and embrace technological innovations. Simultaneously, the geographical location of users introduces contextual nuances, reflecting regional disparities in technology adoption and readiness. This combined influence, emanating from age and location, consequently moulds the user's Behavioral Intention to Use the AQMS application. By recognizing and analyzing these intersecting demographic variables, we gain a more comprehensive understanding of the factors shaping users' readiness and intentions toward embracing the AQMS application for air quality monitoring.

4.5. Theoritical contributions

Our study's theoretical contribution is underscored by the novel integration of UTAUT2, BIU, and TR frameworks, which has not been extensively explored in the context of air quality monitoring technologies. This integration provides fresh insights into user acceptance and engagement, particularly for applications like AQMS that lie at the intersection of technology and environmental health. The empirical data from the AQMS dataset presented in 1, showcasing the application's real-time air quality monitoring capability, forms the backbone of our theoretical advancement. We posit that the ability to deliver real-time environmental data is a crucial determinant of technology readiness and user behavioral intention. This premise has significant theoretical implications, as it suggests that instantaneity in data availability can be a critical factor influencing the acceptance and sustained use of such technologies.

Moreover, our research brings to light the geographical nuances in technology adoption by examining responses from various regions within Indonesia. The empirical evidence pointing to the heightened concern for air quality in Tangerang, for instance, suggests that geographical context is a significant factor in technology acceptance models. This finding enriches the theoretical model by emphasizing the role of location-specific environmental awareness and the need for regionally tailored approaches to technology deployment. Through these theoretical lenses, our research delivers meaningful contributions that extend beyond mere brand or product analysis, offering a more profound understanding of how and why technologies like AQMS are adopted for environmental monitoring. This understanding is vital for driving forward public health initiatives and environmental policies, especially in areas heavily affected by air pollution.

4.6. Managerial implications

4.6.1. Research and future research directions

Our study enhances the existing body of knowledge by elucidating the factors that influence user behavior in the context of AQMS. The substantial impact of PE, SI, HM, HB, and TR on BIU provides fresh insights for academic research. These findings lay a groundwork for future studies to delve deeper into understanding user engagement with environmental monitoring technologies, particularly focusing on the dynamics of habit formation and technology readiness in influencing sustained technology usage. Furthermore, our identification of Effort Expectancy (EE), Facilitating Conditions (FC), and Price Value (PV) as non-significant factors invites future investigations to reassess these elements under different contexts or with modified methodologies, potentially offering new perspectives on their roles in technology adoption.

4.6.2. Practical implications for technology development and adoption

This research offers actionable insights for both users and developers of AQMS. By understanding the key factors that enhance user interest and engagement, such as PE, SI, HM, HB, and TR, individuals and organizations can make more informed decisions about adopting and integrating these technologies into daily practices. For developers, this study acts as a guide to refine AQMS design and functionality, ensuring that product features directly meet user needs and preferences, which is crucial for boosting adoption rates and user satisfaction. Strategically enhancing AQMS features to align with user expectations not only fosters intrinsic motivation but also encourages habitual use, ultimately leading to better health and environmental outcomes. These enhancements should focus on improving user interfaces and interactions to make the technology more engaging and less cumbersome, potentially addressing the unexpected findings regarding EE.

4.6.3. Societal implications and policy recommendations

Our findings inform government entities and policymakers involved in environmental health initiatives at the societal level. The identified factors influencing user behavior provide a robust basis for developing policies and interventions aimed at promoting the widespread adoption of AQMS. Tailored strategies that leverage the positive impacts of PE, SI, HM, HB, and TR can facilitate broader societal engagement with air quality monitoring, thereby enhancing public health and environmental sustainability. The societal impact of our research extends beyond technology adoption, fostering greater awareness and proactive behavior concerning air quality issues. This can lead to a more informed and environmentally conscious populace, ultimately contributing to the collective success of environmental sustainability efforts.

5. Conclusion

This study makes a noteworthy theoretical contribution by introducing the TR dimension within the context of the UTAUT2 model, specifically applied to a consumer environment. Incorporating TR into the model enhances the framework's capacity to comprehensively explore acceptance behavior and intention to use, providing a more thorough understanding of individual intentions toward adopting

AQMS. Furthermore, our findings underscore the substantial impact of several dimensions, including PE, SI, HM, H, and TR, on BIU regarding air quality monitoring with AQMS. Result Variable PE delves into how well AQMS will perform and whether it will effectively meet user's needs. The study reveals that if users believe AQMS will help them monitor air quality accurately and effortlessly, they are more likely to use it. **SI**, reflecting the influence of peers, social norms, and group dynamics, plays a significant role in adopting AQMS. Users witnessing others in their social circles using and recommending the app are more inclined to try it themselves. HM measures the degree to which users enjoy using the AQMS mobile application. A satisfying and enjoyable experience increases the user's likelihood of using the app. HB emphasizes that using the app involves integrating it into the user's daily routines, contributing to consistent usage over time. In the TR dimension, this research identifies innovativeness, discomfort, and insecurity as factors positively impacting the AQMS mobile application, highlighting the dynamic nature of technology readiness.

These findings robustly support our model, showcasing the acceptance of user technology readiness for the AQMS mobile application and laying the foundation for a better understanding of AQMS mobile application adoption. Strengthening the model's ability to explain and predict user behavior contributes to a more comprehensive understanding of user actions, elucidating 75% BIU variations. However, recognizing the inherent limitations of this study, specific recommendations for future research could include exploring additional factors that might influence user acceptance, such as external contextual factors, cultural nuances, or the impact of long-term usage on behavioral intentions. Further investigation into strategies to address initial apprehensions, enhance user education, and refine user interfaces could also contribute to developing more effective and user-friendly environmental monitoring applications.

The findings of this study bear significant implications for both research and practical applications in air quality monitoring. From a research perspective, our investigation highlights the critical role of Technology Readiness in accepting AQMS, suggesting a fertile ground for future studies to explore the nuanced interactions between technological readiness and environmental consciousness. Future research could extend beyond the comparative studies across different geographical and socio-economic landscapes, providing a global perspective on the adoption of AQMS. Practically, this study underscores the importance of integrating technology acceptance models in designing and implementing AQMS to enhance user engagement and effectively address air pollution challenges. Therefore, policymakers and technology developers should consider these insights to tailor air quality initiatives that resonate with the public's readiness and acceptance, paving the way for more sustainable environmental practices.

Disclosure statement

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Appendix A. AQMS characteristic's questions

1. E-mail Address
2. Identity:
   - Name
   - Age
   - Gender
   - Country
   - No Handphone
   - University
3. Concern About Air Quality:
   - Very Caring
   - Neutral
   - Indifferent

Appendix B. The constructs and measurement items for UTAUT2 construct

Questionaire AQMS		
8 Variable	22 Questionnaire	10 References
Effort Expectancy (EE)	It is easy for me to become an expert at using the AQMS mobile application	Fleury et.al
	I expect the AQMS mobile application would be easy to use	
	My interaction with AQMS would be clear and understandable.	
Performance Expectancy (PE)	Using the AQMS mobile application helps me achieve and prepare for health protection from PM 2.5 easier.	Ong et.al
	Using the AQMS mobile application helps me prepare and understand protection from PM 2.5 daily.	Genser et.al
	I found the AQMS mobile application is helpful to see air quality	
Social Influence (SI)	The important persons in my life think I should use the AQMS mobile application.	Genser et.al
	The important person in my life who uses the AQMS mobile application makes my interested to use it.	

Appendix C. The constructs and measurement items for TR construct

Questionaire AQMS - TR Constuct	
4 Factor	12 Questionnaire
Optimism	I believe that using the AQMS will significantly contribute to improving air quality awareness.
	I am optimistic about the positive impact that AQMS will have on my understanding of environmental conditions.
	I feel confident that AQMS will provide valuable insights for better decision-making.
Innovativeness	I am open to trying out new features or updates introduced in the AQMS
	I consider myself an early adopter of technological advancements, including those related to environmental monitoring
	I am willing to explore and use innovative feature that the AQMS may introduce in the future.
Discomfort	I feel some discomfort or hesitation in using the AQMS to monitor environmental conditions.
	The complexity of features in the AQMS contributes to my discomfort or unease while using the application.
	There are specific aspects of the AQMS that make me feel uneasy or uncertain.
Insecurity	I am concerned about the security and privacy of my data when using the AQMS.
	I worry about potential risks or vulnerabilities associated with the integration of technology in environmental monitoring applications.
	Specific security-related aspects of the AQMS raise concerns for me.