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Understanding Data-Driven Analytic Decision Making on Air Quality Monitoring an Empirical Study

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ABSTRACT

Air quality monitoring is increasingly relying on data-driven analytic decision-making tools to provide accurate and timely information, forming **the background** of this study. **The objective** is to understand the factors influencing the adoption and usage behavior of these tools using the Unified Theory of Acceptance and Use of Technology (UTAUT2) model. **The method** involves incorporating UTAUT2 constructs Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Price Value (PV), Hedonic Motivation (HM), and Habit (H), alongside external variables such as Considered Risk (CR) and Considered Trust (CT). Data from 287 respondents were analyzed to assess their impact on Behavior Intention (BI) and Usage Behavior (UB). **The results** demonstrate that both trust and risk considerations significantly affect user behavior, underscoring the need to address these factors to enhance the adoption of air quality monitoring systems. **In conclusion**, this research provides valuable insights for developers and policymakers on improving the implementation and acceptance of data-driven technologies in environmental monitoring, thereby contributing to more effective air quality management.

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1. INTRODUCTION

The rapid development of technology has significantly transformed various sectors, including environmental monitoring, where data-driven analytic decision-making tools are becoming increasingly essential [1–3]. Air quality monitoring, a critical component of environmental health, relies heavily on the accuracy and timeliness of data to inform policy decisions, mitigate risks, and protect public health [4–6]. The necessity for sophisticated monitoring systems is more important than ever due to growing worries about air pollution and its detrimental impact on human health [7]. These systems not only provide real-time data but also enable predictive analysis that can forecast pollution trends and potential health impacts [8, 9]. However, the effectiveness of these technologies is contingent upon their widespread adoption and consistent usage by stakeholders, ranging from policymakers to the general public [10–12]. To optimize the use of these data-driven technologies and increase their impact on air quality management, it is essential to comprehend the variables that drive their acceptance and usage patterns [13, 14].

The UTAUT2 model offers a strong structure for studying factors that influence technology adoption and usage behavior [15]. UTAUT2 expands upon the initial UTAUT framework by including extra elements like HM, PV, and H, which hold particular importance in the realm of individual technology adoption. This theory suggests that PE, EE, SI, and FC play a crucial role in impacting BI and UB. Additionally, the presence of outside factors such as CR and CT is essential in air quality monitoring, as users' trust in data security and technology reliability can significantly influence their readiness to utilize these systems [16–18]. This study aims to offer a thorough insight into the factors that promote or impede the use of data-driven analytic tools in air quality monitoring by combining these variables [19, 20].

Although there is a rising interest in air quality monitoring technologies, there is a scarce amount of empirical research investigating the adoption and usage behavior of these tools using the UTAUT2 framework [21–23]. Previous research has primarily examined the technical components of these systems, like sensor precision and data algorithms, while neglecting the human elements that impact their acceptance [24]. This literature gap underlines the importance of taking a comprehensive approach that takes into account both the technical and behavioral aspects of monitoring air quality [25–27]. The current study aims to fill this void by providing an understanding of how end-users perceive and use data-driven analytical decision-making tools, thus adding to the existing knowledge base [28, 29]. The results of this study will greatly impact the development and implementation of air quality monitoring systems, offering advice to developers, policymakers, and other interested parties on ways to improve the integration and efficiency of these technologies in environmental supervision [30–32].

2. LITERATURE REVIEW

2.1. Data-Driven Decision Making in Environmental Monitoring

Air quality management now relies heavily on data-driven decision-making (DDDM) in its operations. Utilizing advanced analytics and big data technologies can lead to timely, data-driven decisions essential for mitigating negative environmental and health impacts of air pollution [33]. Current research highlights the increasing contribution of DDDM to improving the precision and dependability of air quality forecasts. For instance, it was shown by [34] that using machine learning models that have been trained on sizable datasets greatly enhances the capacity for prediction of air quality monitoring systems Moreover, the deployment of Internet of Things (IoT) devices and cloud-based analytics has enabled real-time data processing, further refining the decision-making process [35]. These developments highlight how DDDM has the potential to completely transform air quality management by offering useful insights that were previously inaccessible through conventional techniques.

2.2. Artificial Intelligence in Environmental Monitoring

Artificial Intelligence (AI) has become a powerful instrument in monitoring the environment, providing notable progress in the precision, productivity, and promptness of data gathering and examination [36, 37]. AI has the ability to analyze vast amounts of data from different sources like sensors, satellite images, and environmental databases in order to offer immediate information about environmental situations [38]. Machine learning algorithms in air quality monitoring have the ability to forecast pollutant levels and detect patterns in data that may not be visible with traditional analysis techniques. AI-powered technology is able to automatically identify irregularities in the environment, which leads to quicker and more knowledgeable decisions when addressing environmental shifts.

Despite the clear benefits, there are challenges associated with integrating AI into environmental monitoring systems. The consistency and quality of the data used to feed AI models is one of the main problems [39]. Environmental data can be fragmented, incomplete, or inconsistent, which can undermine the accuracy of AI-based predictions. Additionally, the integration of AI with existing environmental monitoring infrastructures requires significant investments and strong policy support to ensure scalability and long-term success [40, 41]. Nonetheless, the potential of AI to revolutionize environmental monitoring by enhancing the precision and responsiveness of data analysis makes it a key area for future research and development.

2.3. Application of UTAUT2 in Technology Adoption

Recent studies have commonly utilized the Unified Theory of Acceptance and Use of Technology (UTAUT2) to examine how users accept and interact with new technologies. UTAUT2 enhances the original UTAUT framework by including extra elements like HM, PV, and H, which are especially important for comprehending consumer actions in the modern digital era. Recent research has utilized UTAUT2 in different areas, like environmental monitoring technologies. In a study by [42], the UTAUT2 model was used to investigate how PE and FC impact the adoption of smart home energy management systems, revealing that they are important predictors of BI. In the same way, [43] utilized UTAUT2 to investigate the uptake of mobile health apps and discovered that SI and HM were key factors in user acceptance. These results indicate that UTAUT2 is a strong model for comprehending the various factors that impact technology adoption, especially for researching the use of data-driven analytic tools in air quality monitoring [44].

2.4. External Variables in Technology Adoption: Considered Risk and Considered Trust

While UTAUT2 provides a comprehensive framework for examining technology adoption, the inclusion of external variables such as CR and CT can offer deeper insights into user behavior. CR refers to the perceived potential negative consequences of using a technology, which can significantly hinder adoption. On the other hand, CT relates to the user's confidence in the technology's reliability and security, which can enhance adoption. Recent research has highlighted the importance of these variables in the context of data-driven technologies. For example, [45] found that CR was a major barrier to the adoption of cloud-based services for environmental monitoring, as users were concerned about data privacy and security. Conversely, a study by [46] revealed that high levels of CT positively influenced the adoption of blockchain technologies in environmental data management. These studies highlight the critical role of perceived risk and trust in shaping user behavior, particularly in the adoption of emerging technologies in sensitive areas such as air quality monitoring.

3. RESEARCH METHODOLOGY

3.1. Research Design

This study adopts a quantitative method to analyze the factors shaping air quality monitoring tool usage and adoption rates. The framework known as the UTAUT2 provides the theoretical foundation for pinpointing the main factors that influence Business Intelligence (BI) and User Behavior (UB) in technology [22]. This research adds two more variables, CR and CT, to the main variables of UTAUT2 (PE, EE, SI, FC, PV, HM, and H) because they are seen as crucial in the air quality monitoring technology field. The study also supports Goal 13 of the SDGs calls for urgent climate action to mitigate its impacts and lower greenhouse gas emissions by addressing how technology adoption in air quality monitoring can contribute to improving environmental sustainability and promoting cleaner air through the use of advanced data-driven tools.

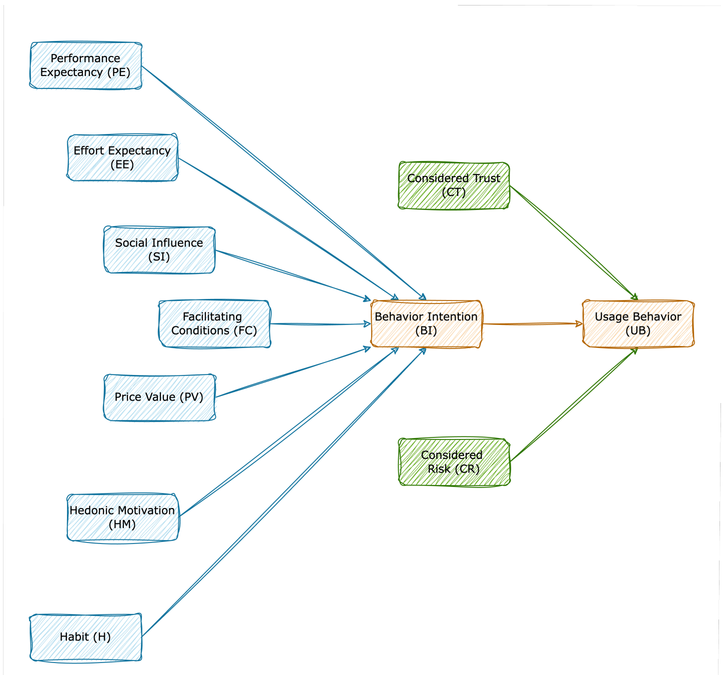

Figure 1. Structural Model

The relationships among these variables are visually represented in Figure 1, which illustrates the hypothesized model tested in this study. This model provides a comprehensive view of the direct and indirect paths connecting the various constructs, helping to elucidate the mechanisms through which these factors influence user behavior in adopting air quality monitoring tools.

3.2. Measurement Items and Survey Design

The table below lists the specific measurement items used for each construct, providing a comprehensive overview of the survey design.

Table 1. Measurement Items

Variable Code	Statement
PE1	The effectiveness of air quality monitoring is increased by using air quality monitoring systems.
PE2	Air Quality Monitoring Systems help accomplish tasks more quickly.
PE3	The productivity of air quality monitoring is increased by air quality monitoring systems.
EE1	Learning to operate Air Quality Monitoring Systems is easy.
EE2	Utilizing Air Quality Monitoring Systems is simple.
EE3	Interaction with Air Quality Monitoring Systems is clear and understandable.
SI1	Important people think that Air Quality Monitoring Systems should be used.
SI2	People who influence behavior prefer that Air Quality Monitoring Systems are used.
SI3	Valued opinions encourage the use of Air Quality Monitoring Systems.
FC1	The necessary resources are available to use Air Quality Monitoring Systems.
FC2	The necessary knowledge is available to use Air Quality Monitoring Systems.
FC3	Air Quality Monitoring Systems are compatible with other used technologies.
PV1	Air Quality Monitoring Systems are reasonably priced.
PV2	Air Quality Monitoring Systems provide good value for the money.
PV3	Air Quality Monitoring Systems offer a good cost-benefit ratio at the current price.
HM1	Using Air Quality Monitoring Systems is enjoyable.
HM2	The use of Air Quality Monitoring Systems is fun.
HM3	Air Quality Monitoring Systems are entertaining.
H1	Using Air Quality Monitoring Systems has become a habit.
H2	Addicted to using Air Quality Monitoring Systems.
H3	Must use Air Quality Monitoring Systems.
BI1	Intend to use Air Quality Monitoring Systems regularly.
BI2	Always try to use Air Quality Monitoring Systems in daily work.
BI3	Plan to continue using Air Quality Monitoring Systems frequently.
UB1	Every day, air quality monitoring systems are employed.
UB2	Air Quality Monitoring Systems are used whenever necessary.
UB3	Air quality is monitored using Air Quality Monitoring Systems.
CR1	Air Quality Monitoring Systems' security is a concern.
CR2	Worried that Air Quality Monitoring Systems might not be secure.
CR3	Air Quality Monitoring Systems raise privacy concerns.
CT1	Trust Air Quality Monitoring Systems to provide accurate information.
CT2	Air Quality Monitoring Systems are believed to be reliable.
CT3	Trust Air Quality Monitoring Systems to perform their intended function properly.

Table 1 the specific measurement items used to assess the various constructs in this study, focusing on the adoption and usage behavior of Air Quality Monitoring Systems. Each item is designed to capture a distinct aspect of the theoretical framework based on the UTAUT2 model, as well as additional variables such as Considered Risk and Considered Trust. The survey was structured to gather respondents' perceptions across multiple dimensions, including PE, EE, SI, FC, PV, HM, H, BI, UB, CT, and CR. The items were carefully worded to ensure clarity and relevance, ensuring that each construct is accurately measured in the context of air quality monitoring technology.

3.3. Data Analysis Techniques

The analysis of PLS-SEM data was performed using SmartPLS software. Due to its capability to manage complex models with a multitude of latent variables and indicators, along with its adaptability to analyze non-normally distributed data, PLS-SEM was chosen for this study. The evaluation process started by assessing the measurement and structural models for both construct validity, reliability, and hypothesis testing. Validity and reliability were assessed using the Fornell-Larcker Criterion, Average Variance Extracted (AVE), and Composite Reliability (CR). Hypothesis tests were performed to determine if the independent variables significantly impacted the dependent variables.

This paper would benefit from a more detailed discussion of the limitations of the PLS-SEM method used in this study. Highlighting potential biases, such as those that may arise from small sample sizes or non-normal data distribution, would increase the transparency of the methodology. Acknowledging these limitations, along with discussing potential weaknesses of the approach, would not only enhance the robustness of the findings but also provide a more balanced perspective on the reliability of the results.

3.4. Population and Sample

The population in this study consists of users of air quality monitoring technologies across various regions represented in table 2. A sample of 350 respondents was initially collected, with 287 valid data points remaining after the screening process. This sample was selected using purposive sampling, where respondents were chosen based on specific criteria relevant to the research objectives, such as their experience in using air quality monitoring technologies and their knowledge of its functionalities.

Table 2. Demographic Population Sample

Demographic Information	**Categories**	**Frequency (n)**	**Percentage (%)**
Gender	Male	145	50.50%
	Female	142	49.50%
Age Group	18-25 years	67	23.30%
	26-35 years	89	31.00%
	36-45 years	79	27.50%
	46-55 years	32	11.10%
	56 years and above	20	7.10%
Experience with Air Quality Monitoring	Less than 1 year	81	28.20%
	1-3 years	115	40.10%
	More than 3 years	91	31.70%
Familiarity with Technology	Low	42	14.60%
	Moderate	129	44.90%
	High	116	40.40%

The sample for this study consists of 287 valid respondents, with a nearly equal distribution of gender: 50.5% male and 49.5% female. The majority of respondents fall within the 26-35 years age group (31.0%), followed by the 36-45 years group (27.5%), 18-25 years group (23.3%), 46-55 years group (11.1%), and those aged 56 years and above (7.1%). Regarding education level, most respondents hold a Bachelor's Degree (58.5%), with 23.7% having a Master's Degree, 11.8% a High School education, and 5.9% a Doctorate Degree. In terms of occupation, 49.8% of the respondents are professionals, followed by students (20.6%), academics/researchers (16.0%), and others (13.6%). Concerning experience with air quality monitoring, 40.1% of respondents have 1-3 years of experience, 31.7% have more than 3 years, and 28.2% have less than 1 year. The sample also shows a balanced distribution of technological familiarity, with 44.9% reporting moderate familiarity, 40.4% reporting high familiarity, and 14.6% reporting low familiarity

4. RESULT

4.1. Outer Model

The reliability and validity of the study's constructs were confirmed through the evaluation of the outer model. Ensuring consistency and accuracy in measuring latent variables relies heavily on this analysis. Both construct reliability, convergent validity, and discriminant validity were assessed.

4.1.1 Construct Reliability and Convergent Validity

We examined Cronbach's alpha, Composite Reliability (rho_a and rho_c), and Average Variance Extracted (AVE) to assess the construct's reliability. These metrics provide insight into the constructs' internal coherence and relationships with other factors.

Table 3. Construct Reliability and Convergent Validity

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.83	0.841	0.898	0.747
CR	0.868	0.869	0.919	0.791
CT	0.772	0.859	0.86	0.673
EE	0.815	0.819	0.89	0.73
FC	0.878	0.887	0.925	0.804
H	0.711	0.767	0.84	0.643
HM	0.821	0.823	0.893	0.737
PE	0.889	0.898	0.931	0.818
PV	0.892	0.893	0.933	0.822
SI	0.864	0.865	0.917	0.787
UB	0.86	0.861	0.915	0.781

The Cronbach's alpha values for all constructs in table 3 are higher than the accepted threshold of 0.7, demonstrating strong internal consistency. As an example, SI has a Cronbach's alpha coefficient of 0.864, while PV shows an even higher alpha of 0.892. The Cronbach's alpha for H is the lowest at 0.711, which, although lower, still falls within the acceptable range. Composite Reliability (rho_c) further confirms the reliability of the constructs, with values ranging from 0.84 (H) to 0.933 (PV). It is important to mention that all constructs surpass the suggested threshold of 0.7 for rho_c, showing that the constructs effectively capture the underlying variables.

The Average Variance Extracted (AVE) values, which assess the variance attributed to the construct relative to measurement error, also support convergent validity. Every AVE value surpasses the 0.5 threshold, indicating that the constructs represent most of the variance in their respective indicators. Especially noteworthy findings are seen in PV, which has an AVE of 0.822, and FC, which has an AVE of 0.804.

The findings show that all the variables employed in this research are dependable and accurate, ensuring the strength of the measurement model. The strong values of Cronbach's alpha, Composite Reliability, and AVE indicate that the constructs are clearly defined and accurately measured, providing a solid basis for further analysis in the inner model.

4.1.2 Discriminant Validity

To ensure that each concept in the model remains unique, discriminant validity must be established. Using the Fornell-Larcker criteria, each construct's square root AVE had to surpass its correlations with other components for assessment.

Table 4. Discriminant Validity Fornell-Larcker Criterion

Variable	BI	CR	CT	EE	FC	H	HM	PE	PV	SI	UB
BI	0.864										
CR	0.753	0.89									
CT	0.715	0.634	0.821								
EE	0.8	0.728	0.62	0.854							
FC	0.784	0.805	0.602	0.799	0.896						
H	0.79	0.698	0.63	0.726	0.79	0.802					
HM	0.802	0.761	0.68	0.813	0.807	0.768	0.858				
PE	0.75	0.771	0.681	0.856	0.74	0.672	0.814	0.904			

Variable	BI	CR	CT	EE	FC	H	HM	PE	PV	SI	UB
PV	0.806	0.806	0.71	0.821	0.869	0.772	0.825	0.819	0.907		
SI	0.779	0.684	0.627	0.861	0.83	0.772	0.806	0.807	0.836	0.887	
UB	0.824	0.786	0.716	0.813	0.742	0.757	0.846	0.805	0.842	0.784	0.884

Diagonal elements in table 4 equal the square roots of AVEs, while off-diagonal values represent correlations. The square root of BI's correlation with AVE is larger (0.864) than its correlations with CR (0.753) and CT (0.715). The square root of UB's AVE is 0.884, greater than its correlations with CR (0.786) and CT (0.716). FC's discriminant validity, as measured by its square root of AVE (0.896), surpasses its highest correlation with PV (0.869). The pattern is consistent for most constructs, suggesting each measures a unique concept within the model.

The outer model analysis confirms the dependability and authenticity of the study's constructs. The soundness of the measurement model relies on the high construct reliability and strong discriminant validity across all variables.

4.2. Inner Model

The inner model, often referred to as the structural model, looks at how the study's latent variables relate to one another. This section will focus on analyzing the Cross Loadings and the results of hypothesis testing, using the path coefficients derived from the Bootstrapping mode.

4.2.1 Cross Loadings

Cross loadings provide insight into how each indicator correlates with its assigned construct compared to other constructs. A well-fitting model should have higher loadings of indicators on their respective constructs than on other constructs, indicating good discriminant validity.

Table 5. Cross Loadings

Variable	BI	CR	CT	EE	FC	H	HM	PE	PV	SI	UB
BI1	0.889	0.697	0.575	0.715	0.769	0.787	0.748	0.697	0.696	0.686	0.741
BI2	0.899	0.716	0.667	0.736	0.684	0.7	0.747	0.702	0.767	0.733	0.74
BI3	0.8	0.523	0.616	0.616	0.566	0.542	0.57	0.532	0.618	0.592	0.652
CR1	0.652	0.877	0.557	0.616	0.699	0.54	0.604	0.634	0.709	0.556	0.679
CR2	0.679	0.908	0.589	0.596	0.717	0.602	0.657	0.642	0.713	0.561	0.678
CR3	0.677	0.883	0.547	0.723	0.731	0.712	0.763	0.772	0.726	0.698	0.737
CT1	0.437	0.303	0.701	0.228	0.346	0.419	0.345	0.306	0.364	0.255	0.362
CT2	0.682	0.682	0.866	0.698	0.601	0.588	0.708	0.734	0.744	0.717	0.761
CT3	0.584	0.464	0.882	0.456	0.469	0.51	0.517	0.509	0.53	0.427	0.522
EE1	0.628	0.497	0.411	0.823	0.582	0.561	0.61	0.597	0.593	0.634	0.629
EE2	0.717	0.738	0.595	0.893	0.762	0.604	0.725	0.806	0.807	0.767	0.759
EE3	0.702	0.616	0.572	0.846	0.693	0.692	0.742	0.778	0.693	0.796	0.691
FC1	0.607	0.648	0.41	0.662	0.893	0.69	0.656	0.561	0.675	0.697	0.551
FC2	0.719	0.692	0.527	0.753	0.913	0.761	0.749	0.669	0.803	0.801	0.656
FC3	0.763	0.808	0.656	0.724	0.884	0.672	0.754	0.738	0.838	0.728	0.765
H1	0.729	0.6	0.55	0.705	0.787	0.905	0.727	0.568	0.724	0.798	0.719
H2	0.46	0.391	0.415	0.279	0.312	0.606	0.437	0.368	0.324	0.301	0.416
H3	0.678	0.658	0.542	0.683	0.717	0.862	0.646	0.648	0.735	0.673	0.646
HM1	0.719	0.706	0.583	0.79	0.744	0.702	0.884	0.754	0.811	0.748	0.77
HM2	0.664	0.547	0.528	0.638	0.714	0.669	0.849	0.619	0.659	0.717	0.634
HM3	0.682	0.702	0.639	0.661	0.619	0.604	0.841	0.719	0.648	0.609	0.772
PE1	0.732	0.698	0.608	0.819	0.697	0.612	0.74	0.921	0.744	0.76	0.719
PE2	0.695	0.698	0.615	0.801	0.676	0.638	0.78	0.916	0.752	0.762	0.761
PE3	0.597	0.698	0.63	0.692	0.63	0.569	0.685	0.875	0.728	0.659	0.705

Variable	BI	CR	CT	EE	FC	H	HM	PE	PV	SI	UB
PV1	0.7	0.743	0.629	0.756	0.772	0.707	0.713	0.727	0.922	0.776	0.788
PV2	0.759	0.788	0.716	0.795	0.794	0.665	0.787	0.844	0.908	0.774	0.784
PV3	0.729	0.659	0.58	0.679	0.795	0.728	0.741	0.651	0.89	0.724	0.717
SI1	0.68	0.617	0.555	0.762	0.781	0.686	0.723	0.75	0.746	0.889	0.68
SI2	0.682	0.616	0.578	0.76	0.728	0.68	0.69	0.721	0.755	0.887	0.693
SI3	0.71	0.587	0.536	0.768	0.701	0.688	0.732	0.678	0.725	0.885	0.712
UB1	0.723	0.695	0.698	0.698	0.612	0.629	0.723	0.675	0.726	0.626	0.879
UB2	0.739	0.634	0.563	0.75	0.648	0.657	0.753	0.717	0.723	0.749	0.867
UB3	0.725	0.752	0.633	0.711	0.707	0.721	0.769	0.743	0.782	0.708	0.905

As shown in table 5, the indicators generally exhibit higher loadings on their respective constructs, which is consistent with the expected measurement model. For instance, the indicators BI1, BI2, and BI3, which belong to the BI construct, have loadings of 0.889, 0.899, and 0.8 on their own construct, respectively. These values are significantly higher than their cross-loadings on other constructs, such as CR (0.697, 0.716, and 0.523, respectively) and CT (0.575, 0.667, and 0.616, respectively). Similarly, the CR construct indicators CR1, CR2, and CR3 show strong loadings of 0.877, 0.908, and 0.883 on their construct, compared to their cross-loadings on other constructs like BI (0.652, 0.679, and 0.677, respectively). This pattern is repeated across most constructs, indicating good discriminant validity.

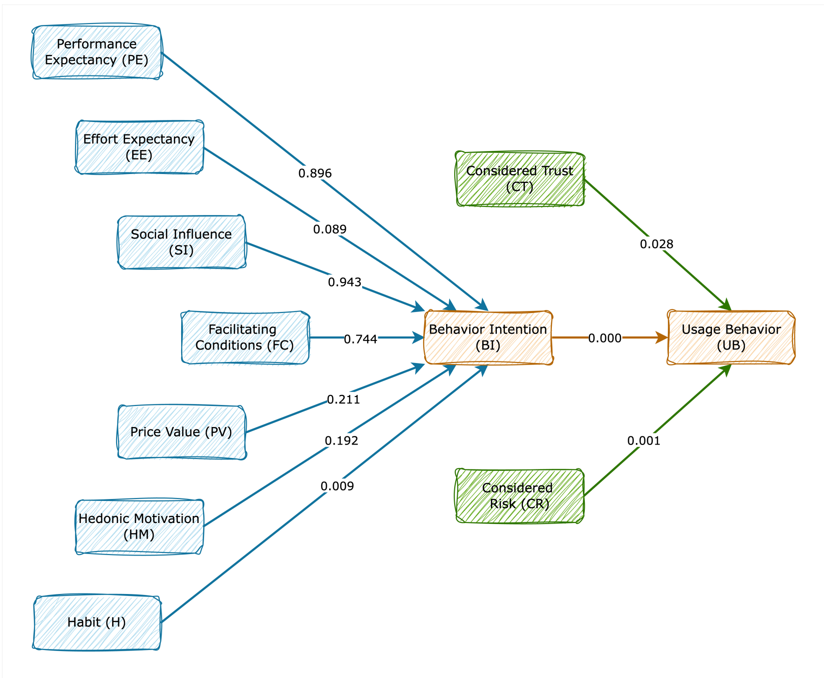

Figure 2. Structural Model

The structural model with path coefficients and R² values is shown in Figure 2, providing a visual depiction of the connections between the components. The path coefficients indicate the strength of the connections between variables, such as the influence of Habit (H) on Behavioral Intention (BI) with a coefficient of 0.285, and the strong impact of BI on Usage Behavior (UB) with a coefficient of 0.431. Other variables, like Performance Expectancy (PE) and Effort Expectancy (EE), show weaker effects on BI with coefficients of 0.023 and 0.247, respectively. The model also reveals that Considered Risk (CR) and Considered Trust (CT) significantly affect UB, with path coefficients of 0.340 and 0.192.

The R² values in the model show that 76.2% of the variance in BI is explained by the independent variables ($R^2 = 0.762$), while 76.0% of the variance in UB is accounted for by BI, CR, and CT ($R^2 = 0.760$).

The figure also displays the loadings of each indicator on its respective construct, such as PE1 (0.921) and BI1 (0.889), which reflect the reliability of these indicators in measuring the intended constructs. This model provides a clear overview of how the constructs interact and influence each other in the context of Air Quality Monitoring Systems adoption and usage.

4.2.2 Summary of Hypotheses Testing Results

The hypotheses testing results provide insights into the significance of the relationships between the latent variables. These relationships are analyzed using the path coefficients, which are derived from the Bootstrapping mode. Significant relationships are determined by examining the t-statistics and p-values.

Table 6. Hypothesis Testing Results

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|0/STDEV|)	P values
EE ->UB	0.107	0.104	0.07	1.517	0.129
FC ->UB	0.022	0.025	0.07	0.318	0.75
H ->UB	0.123	0.118	0.048	2.565	0.01
HM ->UB	0.082	0.077	0.065	1.253	0.21
PE ->UB	0.01	-0.015	0.077	0.129	0.898
PV ->UB	0.075	0.086	0.064	1.167	0.243
SI ->UB	-0.006	0.019	0.086	0.07	0.944

The outcomes of the hypothesis testing are displayed in table 6. An example is the significant connection between BI and UB, showing a strong positive impact with a path coefficient of 0.431, t-statistic of 5.166, and p-value of 0.000. There is also a notable connection found between CR and UB, with a path coefficient of 0.34, t-statistic of 3.35, and p-value of 0.001. This indicates that the perceived risk is a major factor in determining users' interactions with air quality monitoring technology.

Nevertheless, certain relationships do not have a significant statistical value. In this case, the coefficient for the path from FC to BI is 0.052, with a t-statistic of 0.326 and a p-value of 0.744, suggesting that FC might not have a considerable influence on BI in this scenario.

In conclusion, the inner model examination uncovers numerous noteworthy connections among constructs, particularly in the relationships from BI to UB, and from CR and CT to UB. These results emphasize how user perceptions play a crucial role in the acceptance and utilization of data-based air quality monitoring technologies. The findings suggest that in this particular situation, certain commonly regarded factors like FC and SI may not carry as much weight.

4.3. Testing of Mediation Effects

Mediation effects refer to the indirect effects that one variable has on another through a mediating variable. In this study, the mediation effects were tested to understand how certain independent variables influence the dependent variable UB through an BI. The results of the mediation tests are summarized in table 7.

4.3.1 Indirect Effects

The indirect effects were evaluated using the bootstrapping method, which provides robust estimates of the mediation paths. The significance of these paths is determined by examining the t-statistics and p-values.

Table 7. Mediation Effects Testing

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|0/STDEV|)	P values
EE ->UB	0.107	0.104	0.07	1.517	0.129
FC ->UB	0.022	0.025	0.07	0.318	0.75
H ->UB	0.123	0.118	0.048	2.565	0.01
HM ->UB	0.082	0.077	0.065	1.253	0.21

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|0/STDEV|)	P values
PE ->UB	0.01	-0.015	0.077	0.129	0.898
PV ->UB	0.075	0.086	0.064	1.167	0.243
SI ->UB	-0.006	0.019	0.086	0.07	0.944

As shown in table 7, the mediation effect of H on UB through BI is significant, with an indirect effect coefficient of 0.123, t-statistic of 2.565, and p-value of 0.01. This indicates that H has a meaningful indirect influence on UB, suggesting that users' habitual engagement with the system strongly impacts their actual usage behavior when mediated by their behavioral intention.

Another pathway examined was the mediation effect of EE on UB. The results indicate a positive but non-significant indirect effect with a coefficient of 0.107, t-statistic of 1.517, and p-value of 0.129. This suggests that while EE might influence UB through BI, the effect is not statistically significant in this model. The FC variable shows an even weaker indirect effect on UB, with a coefficient of 0.022, t-statistic of 0.318, and p-value of 0.75. This result indicates that FC do not significantly mediate the relationship between these variables. On the other hand, HM exhibits a positive indirect effect of 0.082 on UB, but this effect is not significant with a t-statistic of 1.253 and a p-value of 0.21. This indicates that while users may derive enjoyment or satisfaction from the system, this motivation does not significantly translate into actual usage behavior through their behavioral intentions. For PE, the mediation effect is minimal and not significant, with a coefficient of 0.01, t-statistic of 0.129, and a p-value of 0.898. Similarly, PV shows a non-significant indirect effect on UB, with a coefficient of 0.075, t-statistic of 1.167, and p-value of 0.243.

Lastly, SI exhibits a negative and non-significant mediation effect on UB with a coefficient of -0.006, t-statistic of 0.07, and p-value of 0.944, suggesting that social factors do not significantly influence users' behavior through their intentions.

4.3.2 Interpretation of Results

The results from the mediation analysis suggest that Habit (H) is the most significant mediator among the variables tested, indicating that habitual usage of the system strongly influences the actual usage behavior via users' behavioral intentions. This underscores the importance of fostering user habits to ensure consistent engagement with the technology. These findings contribute to the existing body of knowledge in the fields of AI and environmental monitoring by demonstrating how habitual behavior plays a key role in the sustained use of data-driven technologies for air quality monitoring.

On the other hand, variables such as FC, EE, and PV do not show significant mediation effects, indicating that these factors may influence UB directly rather than through BI. Moreover, the non-significant mediation effects of PE and SI suggest that these factors may not play a critical role in shaping actual system usage when mediated by behavioral intentions. These findings could have important implications for future research and policy-making, particularly in designing interventions and strategies to promote technology adoption. Understanding which factors have the most influence on user behavior could guide the development of more effective AI-driven solutions in environmental monitoring and inform future policies aimed at increasing the adoption of these technologies.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide valuable insights for managers and decision-makers involved in the development and implementation of data-driven air quality monitoring technologies. First, the significant role of Habit in influencing UB highlights the importance of designing systems that encourage frequent and consistent use. Managers should focus on creating user-friendly interfaces and providing continuous support to foster habitual engagement with the technology. This can be achieved through user training, effective onboarding, and regular updates that enhance user experience and system efficiency.

Additionally, the findings suggest that PE and SI have a relatively minor effect on user satisfaction and behavior in this context. Managers should, therefore, shift their focus from merely emphasizing system performance and peer influence to more critical factors like FC and CT. Building user trust in the technology's accuracy and security, particularly in sensitive fields like environmental monitoring, is crucial. Organizations must ensure that the technology is secure, reliable, and provides real-time, accurate data to foster greater user trust and confidence. Furthermore, incorporating feedback from users to continuously improve the system's functionality and alignment with user needs will strengthen long-term adoption and utilization, contributing to environmental sustainability goals.

6. CONCLUSION

The findings of this study highlight that Habit (H) is the most significant variable influencing User Satisfaction in the context of data-driven air quality monitoring technologies. The mediation analysis reveals that H not only directly impacts Usage Behavior (UB) but also serves as a strong mediator between Behavioral Intention (BI) and actual usage. This underscores the critical role that habitual engagement plays in user satisfaction, suggesting that fostering user habits through consistent and positive experiences can significantly enhance the adoption and sustained use of these technologies.

In contrast, variables such as Effort Expectancy (EE), Facilitating Conditions (FC), and Price Value (PV) were found to have a weaker and non-significant impact on User Satisfaction when mediated by BI. Social Influence (SI) and Performance Expectancy (PE) were also non-significant, suggesting that peer influence and users' expectations of performance do not substantially affect their satisfaction with the technology. However, this study differs from previous research in its application of the UTAUT2 model to air quality monitoring technologies, where certain constructs, such as Habit, play a more dominant role. The comparison with prior studies highlights the unique context of this study and suggests that some variables, traditionally significant in other technological contexts, may not have the same influence here.

Despite these insights, this study has some limitations that should be acknowledged. The sample size, while adequate, may not fully capture the diversity of user experiences across different regions and technological environments. Additionally, while the application of UTAUT2 in this context is relatively new, further emphasis could be placed on explicitly comparing the results to previous studies in similar fields to better highlight the model's novel application. Future research could expand on this by exploring additional factors, such as technological anxiety or data trust, and by conducting longitudinal studies to understand how user satisfaction evolves over time, as well as performing comparative studies across different technological contexts to assess the generalizability of these findings.

7. DECLARATIONS

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7.2. Author Contributions

Interpretation: UR; Approach: IS and DM; Program: QA; Confirmation: IS and DM; Thorough Examination: QA and UR; Study: QA; Materials: UR and QA; Data Management: IS; Initial Drafting: QA; Revision: UR and QA; Presentation: QA; All the authors, UR, DM, IS, and QA, have reviewed and approved the manuscript for publication.

7.3. Data Availability Statement

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

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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