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# A Framework of Adoption Factors for Successful IoT Implementation in Greenhouse Gas Emission Monitoring in the UAE

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**Abstract**

This study presents the development of a framework that identifies and evaluates the key adoption factors for successfully deploying Internet of Things (IoT) technologies in the monitoring of greenhouse gas emissions within the United Arab Emirates. A unique aspect of this research lies in its focus on a specific sector, involving 384 employees from the UAE's Department of Hazard Forecasting, Monitoring, and Control (HFMC), who are directly engaged with IoT-based emissions monitoring. The study employs a robust methodological approach, using Partial Least Squares (PLS) and Structural Equation Modelling (SEM) with SmartPLS software to analyze both the measurement and structural components of the model. The findings reveal that Interoperability and Compatibility (IC) is the most influential factor in greenhouse gas monitoring and utilization (GMAU), followed by Data Analytics and Processing (DAP) and Data Security and Privacy (DSP). Interestingly, Sensor Accuracy and Calibration (SAAC) and Connectivity and Network Infrastructure (CNI) were found to have negligible impacts. This study underscores the crucial importance of advanced data analytics capabilities and stringent data security measures in ensuring the effectiveness of IoT in emissions monitoring. Furthermore, it highlights that enhancing IC significantly boosts monitoring efficiency, providing novel insights into the factors that drive IoT adoption for environmental monitoring. The study's findings also demonstrate that the proposed framework has strong predictive relevance, as evidenced by $Q^2$ values exceeding 0.35, which further reinforces its practical applicability. This research contributes novel insights into the deployment of IoT for environmental monitoring, offering a comprehensive guide for improving emissions tracking in the UAE.

**Keywords:** theoretical framework, validated framework, IoT, greenhouse gas emission

## 1. Introduction

Efforts to reduce greenhouse gas (GHG) emissions have evolved from environmental concerns to national priorities, with the 1992 Rio UN Conference and the UN Framework Convention on Climate Change (UNFCCC) shaping global approaches to air pollution. In the UAE, the oil and gas sector contributes over 90% of total emissions, making effective mitigation measures essential. Rising $CO_2$ levels exacerbate global warming and water scarcity, highlighting the need for accurate GHG monitoring to support climate action (IPCC, 2021). Effective emission control depends on reliable data collection and supportive policies that encourage technology adoption, yet many countries, including the UK, Germany, and the Netherlands, struggle with inadequate monitoring, resulting in environmental and health risks (Hao et al., 2025). Without robust controls, climate-related challenges such as extreme weather events and rising sea levels will continue to threaten sustainable development (Reisinger et al., 2025).

The adoption of the Internet of Things (IoT) for emissions monitoring offers significant potential by enabling real-time data collection, remote sensing, and advanced analytics across extraction, processing, and transportation operations (Marzouk, 2025; Climate Central, 2022). However, widespread implementation faces several adoption barriers, including data security vulnerabilities, uncertain returns on investment, immature technologies, high implementation costs, and compatibility challenges with existing oil and gas infrastructure (Badhan et al., 2025; Ali et al., 2025). Overcoming these barriers requires a comprehensive understanding of the key adoption factors that drive successful IoT deployment, supported by collaboration, investment in advanced technologies, and robust data governance. When effectively implemented, IoT-generated data can enhance regulatory compliance, inform evidence-based policy decisions, and accelerate the UAE's transition toward low-carbon energy (Dizdarević et al., 2019; Santos et al., 2021).

In parallel, the UAE has articulated ambitious climate commitments aligned with global frameworks such as the Paris Agreement. Within this national agenda, Abu Dhabi National Oil Company (ADNOC) has established clear decarbonization targets, including a 25% reduction in GHG emissions intensity by 2030 and the capture of 5 million tonnes of $CO_2$ annually through carbon capture and enhanced oil recovery initiatives. ADNOC has also adopted the Energy Management System (EnMS) in compliance with ISO 50001:2018 standards, with the objective of achieving a 5% improvement in energy efficiency by 2025 (Dizdarević et al., 2019). These initiatives highlight the growing importance of advanced monitoring frameworks that not only leverage IoT capabilities but also address sector-specific adoption requirements, such as technology readiness, infrastructure integration, cybersecurity resilience, cost-effectiveness, and alignment with national climate policies.

The proposed framework is novel in its contextualized application of IoT adoption to greenhouse gas monitoring within the UAE oil and gas sector. Rather than treating IoT adoption as a generic technological process, the framework explicitly bridges conventional fossil-fuel operations with emerging low-carbon and digital technologies. Its effectiveness is grounded in its ability to ensure accurate and reliable emissions data, mitigate cybersecurity risks, demonstrate economic feasibility, enable seamless integration with existing operational systems, and support regulatory compliance. By addressing these critical adoption factors, the framework positions IoT as a strategic enabler of efficient GHG monitoring, sustainable industrial operations, and the UAE's broader energy transition objectives.

Overall, the novelty of this research lies in its sector-specific and context-sensitive integration of IoT adoption principles with environmental monitoring requirements in the UAE. Unlike existing global models that generalize IoT adoption across industries, this study develops a tailored framework that integrates environmental, technological, and policy dimensions unique to the UAE oil and gas industry. In doing so, it bridges the gap between theoretical technology adoption models and their practical application in real-world emission control systems, offering both academic contributions and actionable insights for industry stakeholders and policymakers.

## 2. Formulation of Theoretical Framework

The theoretical framework for this study is grounded in Everett Rogers' Diffusion of Innovations (DOI) theory, which provides a structured lens for understanding how new technologies, such as IoT for greenhouse gas (GHG) monitoring, are adopted within organizations and society (Rogers, Singhal, & Quinlan, 2014). Building on this foundation, the framework identifies five key adoption factors that critically influence the successful implementation of IoT-based GHG monitoring in the UAE: Sensor Accuracy and Calibration, Data Security and Privacy, Connectivity and Network Infrastructure, Interoperability and Compatibility, and Data Analytics and Processing.

These factors were selected based on their relevance to the UAE's environmental and technological context, where oil and gas operations, infrastructure constraints, and regulatory requirements create unique adoption challenges. The dependent variable in this study is the effectiveness of GHG monitoring, reflecting the ability to produce accurate, reliable, and actionable environmental data, as illustrated in Figure 1.

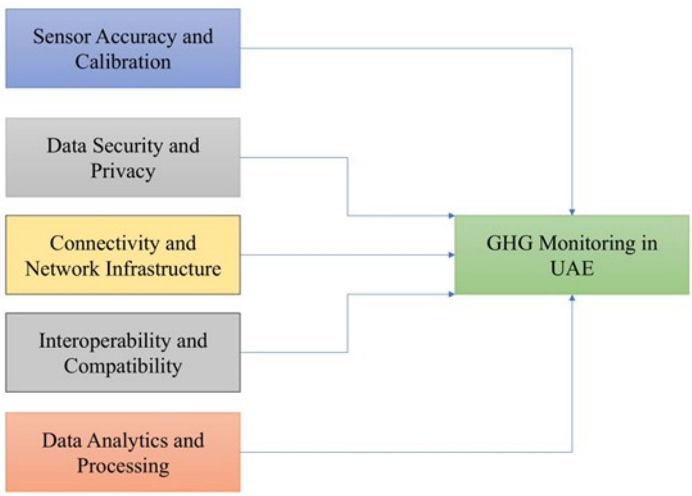


Figure 1. Theoretical framework

The novelty of this framework lies in its contextualized adaptation of the DOI theory to the UAE, a region characterized by specific environmental, technological, and regulatory dynamics. Unlike prior studies that examine IoT adoption in general industrial or environmental contexts, this framework integrates five interrelated factors that collectively address the technical, organizational, and policy dimensions of IoT implementation for GHG monitoring. This approach offers a localized and holistic perspective, providing insights into both the enablers and barriers to effective technology adoption in the UAE.

Methodologically, the study advances existing literature by combining DOI theory with quantitative validation using Partial Least Squares Structural Equation Modeling (PLS-SEM). This hybrid approach strengthens theoretical rigor while offering robust empirical evidence on the practical viability and performance of IoT-based environmental monitoring systems.

The practical value of the framework is reflected in its capacity to inform decision-making and implementation strategies. By emphasizing critical elements such as sensor reliability, cybersecurity robustness, network infrastructure readiness, system interoperability, and advanced data analytics, the framework ensures that IoT deployments generate accurate, secure, and actionable environmental data. This, in turn, supports evidence-based policymaking and regulatory compliance, while enhancing the UAE's ability to achieve its GHG reduction targets and broader sustainability objectives. Overall, the framework effectively bridges the gap between theoretical models of technology adoption and real-world implementation, offering meaningful contributions to academic discourse as well as actionable guidance for industry practitioners and policymakers.

## 3. Modelling of Theoretical Framework

To evaluate the theoretical framework, a questionnaire survey was conducted with 384 employees from the UAE's Department of Hazard Forecasting, Monitoring, and Control (HFMC). The respondents were selected based on their involvement in IoT-based greenhouse gas emission monitoring. The collected data was analysed using SmartPLS software, which applies Structural Equation Modelling (SEM) and the Partial Least Squares (PLS) technique. Batra, (2025) recommended this method as it is more suitable for theory development than theory confirmation. The modelling analysis followed several steps. First, the measurement model was assessed to ensure construct reliability and validity (Gaskin et al., 2025).

Second, the structural model was evaluated to test the hypothesized relationships between the independent variables, which include sensor accuracy and calibration, data security and privacy, connectivity and network infrastructure, interoperability and compatibility, and data analytics and processing, with the dependent variable, Greenhouse Gas (GHG) Monitoring (Troiville et al., 2025). Finally, the goodness-of-fit indices were reviewed to validate the overall model fit (Costa et al., 2025). This comprehensive analysis provided a strong framework for understanding the factors influencing the successful implementation of IoT in greenhouse gas emission monitoring in the UAE (Fonseca Vargas & Gabardo-Martins, 2025).

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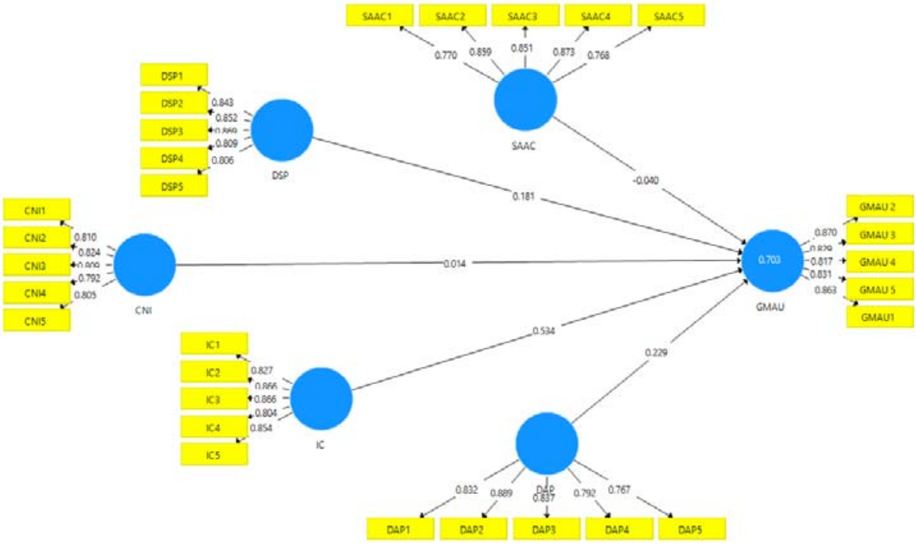


Figure 2. The model after path analysis

Figure 2 shows that IC has the strongest positive effect on GMAU (β = 0.534), followed by DAP (β = 0.229), DSP (β = 0.181), and CNI (β = 0.104). SAAC has a slight negative effect (β = –0.040). All constructs are measured by high-loading indicators (>0.80), confirming strong reliability and convergent validity. The model highlights IC as the most critical predictor of GMAU.

*3.1 Construct Reliability and Validity*

Construct reliability assesses the internal consistency of the items that measure a particular construct, often evaluated using indicators such as Cronbach's Alpha and Composite Reliability. Cronbach's Alpha values above 0.70 indicate acceptable reliability, while values above 0.80 are considered good. Construct validity, on the other hand, examines whether the items truly represent the construct they are intended to measure. This is typically assessed through Convergent Validity and Discriminant Validity. Convergent Validity is indicated by Average Variance Extracted (AVE) values exceeding 0.50, meaning that more than half of the variance in the indicators is accounted for by the latent construct (Faishal et al., 2025; Gradillas & Thomas, 2025). The results of construct reliability and validity are presented in Table 1.

Table 1. Results of construct reliability and validity

| Constructs | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|
| CNI | 0.867 | 0.904 | 0.653 |
| DAP | 0.881 | 0.914 | 0.68 |
| DSP | 0.892 | 0.921 | 0.699 |
| IC | 0.898 | 0.925 | 0.712 |
| GMAU | 0.898 | 0.924 | 0.709 |
| SAAC | 0.882 | 0.914 | 0.681 |

The reliability and validity of the constructs were assessed using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). Connectivity and Network Infrastructure (CNI) exhibited a Cronbach's Alpha of 0.867, a Composite Reliability of 0.904, and an AVE of 0.653, indicating strong reliability and validity. Similarly, Data Analytics and Processing (DAP) demonstrated a Cronbach's Alpha of 0.881, a Composite Reliability of 0.914, and an AVE of 0.68, confirming its robustness. For Data Security and Privacy (DSP), the Cronbach's Alpha was 0.892, Composite Reliability was 0.921, and AVE was 0.699, reflecting excellent reliability and validity. Interoperability and Compatibility (IC) had a Cronbach's Alpha of 0.898, a Composite Reliability of 0.925, and an AVE of 0.712, signifying high internal consistency. Greenhouse Gas Monitoring and Use (GMAU) recorded a Cronbach's Alpha of 0.898, Composite Reliability of 0.924, and AVE of 0.709, further supporting strong reliability. Sensor Accuracy and Calibration (SAAC) showed a Cronbach's Alpha of 0.882, Composite Reliability of 0.914, and an AVE of 0.681, confirming robust measurement properties. Since all constructs exceeded the Composite Reliability threshold of 0.70 and the AVE threshold of 0.50, the results validate the measurement model's strength.

### *3.2 Discriminant Validity*

Discriminant Validity ensures that the constructs are distinct and not highly correlated with each other, often verified through the Fornell-Larcker criterion or the Heterotrait-Monotrait Ratio (HTMT) (Batra, 2025). The results of Fornell-Larker test are presented in Table 2.

Table 2. Fornell-Larcker

| Construct | CNI | DAP | DSP | IC | GMAU | SAAC |
|---|---|---|---|---|---|---|
| CNI | **0.808** | | | | | |
| DAP | 0.703 | **0.824** | | | | |
| DSP | 0.715 | 0.637 | **0.836** | | | |
| IC | 0.701 | 0.71 | 0.717 | **0.844** | | |
| GMAU | 0.652 | 0.707 | 0.69 | 0.809 | **0.842** | |
| SAAC | 0.655 | 0.644 | 0.731 | 0.662 | 0.602 | **0.825** |

Table 2 presents the Fornell-Larcker criterion values to assess the discriminant validity of the constructs. The Connectivity and Network Infrastructure (CNI) construct has a square root of the AVE value of 0.808. Data Analytics and Processing (DAP) shows an AVE value of 0.824, with a correlation of 0.703 with CNI. For Data Security and Privacy (DSP), the AVE value is 0.836, correlating with CNI at 0.715 and DAP at 0.637. Interoperability and Compatibility (IC) exhibit an AVE value of 0.844, with correlations of 0.701 with CNI, 0.710 with DAP, and 0.717 with DSP. The Greenhouse Gas Monitoring and Use (GMAU) construct has an AVE value of 0.842, correlating with CNI at 0.652, DAP at 0.707, DSP at 0.690, and IC at 0.809. Lastly, Sensor Accuracy and Calibration (SAAC) show an AVE value of 0.825, with correlations of 0.655 with CNI, 0.644 with DAP, 0.731 with DSP, 0.662 with IC, and 0.602 with GMAU. These results demonstrate that each construct is distinct, indicating good discriminant validity. The results of Heterotrait-Monotrait Ratio are presented in Table 3.

Table 3. Results of Heterotrait-Monotrait Ratio (HTMT)

| **Construct** | **CNI** | **DAP** | **DSP** | **IC** | **GMAU** | **SAAC** |
|---|---|---|---|---|---|---|
| CNI | | | | | | |
| DAP | 0.804 | | | | | |
| DSP | 0.812 | 0.720 | | | | |
| IC | 0.794 | 0.800 | 0.801 | | | |
| GMAU | 0.733 | 0.792 | 0.769 | 0.899 | | |
| SAAC | 0.751 | 0.732 | 0.822 | 0.745 | 0.677 | |

Table 3 shows the results of the Heterotrait-Monotrait ratio (HTMT) test for determining discriminant validity among constructs. Greenhouse Gas Monitoring and Use (GMAU) and Interoperability and Compatibility (IC) have the highest correlation (HTMT = 0.899). Data Security and Privacy (DSP) has a substantial association with Connectivity and Network Infrastructure (CNI) at 0.812, Data Analytics and Processing (DAP) at 0.72, and IC at 0.801. Data Analytics and Processing (DAP) also shows associations with CNI (0.804) and IC (0.8). Sensor Accuracy and Calibration (SAAC) correlate with CNI (0.751), DAP (0.732), DSP (0.822), IC (0.745), and GMAU (0.677). Overall, these HTMT values show adequate discriminant validity, as they are below the threshold of 0.90 for the majority.

### *3.3 Path Strength*

In structural equation modelling (SEM), the path strength, also known as the path coefficient, assesses the link between two variables in the model. A larger path coefficient shows that one variable has a stronger influence on the other. The significance level of a model reveals the statistical validity of the hypothesised relationships, which is typically measured using p-values. A p-value of less than 0.05 normally indicates that the path is statistically significant, confirming that the observed link is unlikely to have occurred by coincidence (Batra, 2025). Table 4 shows the results of path strength generated from hypothesis testing on the model.

Table 4. Results of path strength

| Paths | Original Sample (O) | T Statistics >1.96 | Remark |
|---|---|---|---|
| CNI -> GMAU | 0.014 | **0.195** | Not significant |
| DAP -> GMAU | 0.229 | 2.930 | Significant |
| DSP -> GMAU | 0.181 | 2.327 | Significant |
| IC -> GMAU | 0.534 | 7.193 | Significant |
| SAAC -> GMAU | -0.040 | **0.578** | Not significant |

Table 4 displays the connections between the model's constructs found by hypothesis testing. Sensor Accuracy and Calibration (SAAC) and Connectivity and Network Infrastructure (CNI) are the two minor pathways that lead to GMAU. The other three routes are given a great deal of weight. The most robust of the three routes is Interoperability and Compatibility (IC) to GMAU, with a path strength of 0.534. After that, Data Analytics and Processing (DAP) is transmitted towards GMAU with a path strength of 0.229. Data Security and Privacy (DSP) have a path strength of 0.181 and is associated with GMAU. Increasing the interoperability and compatibility of greenhouse gas monitoring systems can significantly improve their effectiveness.

To ensure the successful implementation of Internet of Things-based greenhouse gas monitoring systems, strict data security and privacy protocols must be implemented, as well as a strong emphasis on strong data analytics and processing. This is necessary to guarantee the success of the implementation. The findings indicate that these essential aspects must be considered to ensure that the Internet of Things (IoT) technology used in environmental monitoring operations in the United Arab Emirates is both effective and reliable.

### *3.4 Model Fitness*

The R square value is a measure of the fitness of a model, and it indicates the proportion of the variance in dependent variables that can be accounted for by independent variables. In structural equation modelling (SEM), the $R^2$ value is a metric frequently used to evaluate the model's fit. This evaluation ensures that the model is accurate. One indication of this is a higher $R^2$ value, which indicates a better fit between the model and the data and an increase in the power of explanation (Troiville et al., 2025). An illustration of the value of the model's $R^2$ can be found in Table 5.

Table 5. R square value of the model

| Dependent construct | R Square |
|---|---|
| GMAU | 0.703 |

Table 5 shows a $R^2$ value of 0.703 for Greenhouse Gas Monitoring and Use (GMAU), indicating that the model explains around 70.3% of the variance. The results indicate that the model's GMAU explanatory powers are strong.

Fit indices of the saturated model, such as SRMR, d_ULS, d_G, Chi-Square, and NFI, are also used to evaluate how well the proposed model fits the data. The indicators displayed offer a thorough assessment of model performance (Batra, 2025). The model's fit indices are displayed in Table 6.

Table 6. Fit indices of the saturated model

| Indices | Saturated Model | Estimated Model |
|---|---|---|
| SRMR | 0.052 | 0.052 |
| d_ULS | 1.249 | 1.249 |
| d_G | 0.706 | 0.706 |
| Chi-Square | 1590.84 | 1590.84 |
| NFI | 0.829 | 0.829 |

The model fitness indices in Table 6 show that the values of the Saturated Model and the Estimated Model are the same. A Standardised Root Mean Square Residual (SRMR) value of 0.052 indicates a robust fit. The difference between the d_ULS value of 1.249 and the d_G value of 0.706 is significant. The Chi-Square score of 1590.84 and the NFI of 0.829 both show that the model fits the data well. The similar values in the two models validate the robustness of the model fit.

*3.5 Model Predictive Relevance*

Batra, (2025) utilize Cross-Validated Redundancy (CVR) to assess the model's ability to predict endogenous constructs through the $Q^2$ value, while Construct Cross-Validated Communality (CVC) evaluates the shared characteristics of each construct to ensure that indicators effectively measure their respective latent components (Fonseca Vargas & Gabardo-Martins, 2025). Both metrics provide essential insights into the model's robustness and measurement accuracy. A high $Q^2$ value in CVR signifies strong predictive relevance, confirming the model's capability to forecast future data points accurately. Similarly, a high $Q^2$ value in CVC indicates that a substantial portion of variance in the indicators is explained by their corresponding latent constructs, reflecting high communality and strong measurement quality.

Table 7. Results of Construct Cross Validated Communality (CVR)

| **Constructs** | | **SSO** | **SSE** | **$Q^2$ (=1-SSE/SSO)** |
|---|---|---|---|---|
| Constructs | SSO | SSE | $Q^2$ (=1-SSE/SSO) | |
| Independent | CNI | 1990 | 1990 | |
| Independent | DAP | 1990 | 1990 | |
| Independent | DSP | 1990 | 1990 | |
| **Dependent** | GMAU | 1990 | 1018.261 | 0.488 |
| Independent | IC | 1990 | 1990 | |

The dependent construct in Table 7, Greenhouse Gas Monitoring and Use (GMAU), has an SSO of 1990 and an SSE of 1018.261, yielding a $Q^2$ value of 0.488. The model demonstrates a reasonable level of predictive relevance for the GMAU construct, as evidenced by a $Q^2$ value exceeding 0.35, which suggests sufficient predictive capability. The score indicates that the model accounts for approximately 48.8% of the variance in GMAU, demonstrating its effectiveness in forecasting outcomes related to this dependent variable.

Table 8. Results of Construct Cross Validated Communality (CVC)

| **Constructs** | | **SSO** | **SSE** | **$Q^2$ (=1-SSE/SSO)** |
|---|---|---|---|---|
| Independent | CNI | 1990 | 1048.902 | 0.473 |
| Independent | DAP | 1990 | 971.505 | 0.512 |
| Independent | DSP | 1990 | 912.077 | 0.542 |
| **Dependent** | GMAU | 1990 | 883.721 | 0.556 |
| Independent | IC | 1990 | 875.612 | 0.560 |
| Independent | SAAC | 1990 | 960.813 | 0.517 |

Table 8 presents the $Q^2$ values for each construct, demonstrating their predictive relevance. The Connectivity and Network Infrastructure (CNI) construct has a $Q^2$ score of 0.473, with a Sum of Squares Observed (SSO) of 1990 and a Sum of Squares Error (SSE) of 1048.902, indicating moderate predictive relevance. The Data Analytics and Processing (DAP) construct shows a $Q^2$ value of 0.512, an SSO of 1990, and an SSE of 971.505, suggesting slightly higher predictive importance. The Data Security and Privacy (DSP) construct exhibits a $Q^2$ score of 0.542, with an SSO of 1990 and an SSE of 912.077, highlighting considerable predictive significance. The dependent construct, Greenhouse Gas Monitoring and Use (GMAU), demonstrates strong predictive relevance with a $Q^2$ value of 0.556, an SSO of 1990, and an SSE of 883.721. Similarly, the Interoperability and Compatibility (IC) construct displays excellent predictive significance with a $Q^2$ score of 0.560, an SSO of 1990, and an SSE of 875.612.

Overall, the validated model demonstrates strong explanatory and predictive capabilities, accounting for 70.3% of the variance in greenhouse gas monitoring effectiveness. The $Q^2$

values above 0.35 confirm the model's predictive relevance, while the SRMR value of 0.052 indicates a robust fit between the hypothesized and observed data. Collectively, these metrics confirm that the proposed IoT adoption framework is not only statistically sound but also practically effective in guiding environmental monitoring strategies in the UAE.

## 4. Validated Framework

According to Saunders, a validated framework is developed after the theoretical or conceptual framework has been validated with empirical evidence (Gradillas & Thomas, 2025). It relies on data collected from observations, surveys, experiments, or other empirical methods. Specifically, the validated framework focuses on testing the relationships and hypotheses defined in the theoretical or conceptual framework using actual data, with a particular emphasis on evidence derived from real-world observations. Consequently, based on the hypothesis testing results in the path strength section, the validated framework for this study is illustrated in Figure 3.

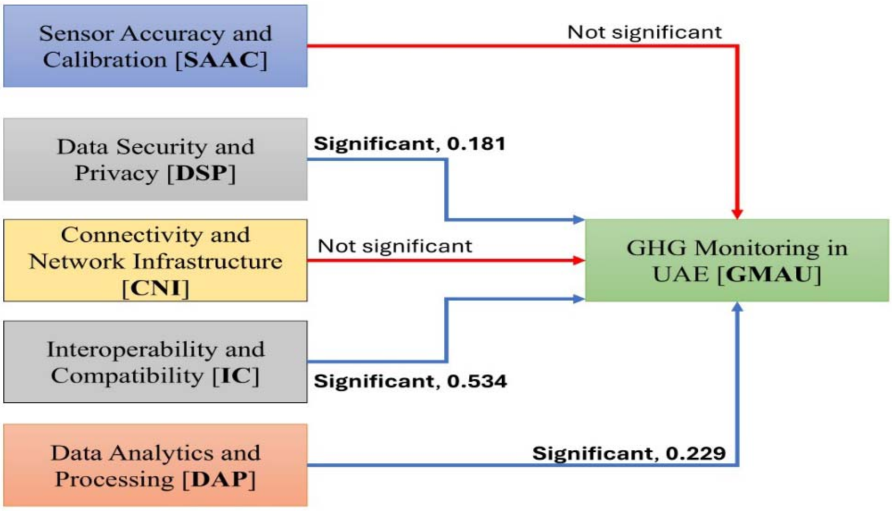


Figure 3. The validated framework

The validated framework highlights significant relationships in greenhouse gas monitoring in the UAE. Significant paths, represented by blue lines, indicate that Data Security and Privacy (DSP), Interoperability and Compatibility (IC), and Data Analytics and Processing (DAP) have a strong impact on Greenhouse Gas Monitoring (GMAU), with path coefficients of 0.181, 0.534, and 0.229, respectively. In contrast, non-significant paths, represented by red lines, include the relationships between Sensor Accuracy and Calibration (SAAC), Connectivity and Network Infrastructure (CNI), and GMAU. This validated framework aligns with and contrasts previous research, offering valuable insights.

The study confirms that DSP, IC, and DAP are critical factors in greenhouse gas monitoring, while SAAC and CNI do not significantly impact GMAU. Prior studies, such as those by

(Salim et al., 2025) and (Samha et al., 2025), emphasize the importance of robust data security and privacy measures in environmental monitoring. These studies found that effective data security policies enhance data reliability and trustworthiness. Consistently, the current framework establishes a strong link between DSP and GMAU, reinforcing the role of data security in greenhouse gas monitoring.

Similarly, (Adeoye, 2025) and (Harum et al., 2024) highlight interoperability and compatibility as essential in IoT systems, noting that seamless integration enhances data collection and processing. The current framework validates this, showing a significant positive impact of IC on GMAU, underscoring the need for efficient system integration. Additionally, studies by (Baharon et al., 2024) and (Vij & Goyal, 2025) stress the role of advanced data analytics in environmental monitoring, demonstrating that sophisticated analytics improve data accuracy and generate meaningful insights. This study supports these findings, confirming a strong relationship between DAP and GMAU, highlighting the necessity of advanced data processing in emission monitoring.

Previous research, including (Pandian & Disney, 2025) and (Aldawsari, 2025), has suggested that sensor accuracy is crucial for reliable data collection in environmental monitoring. However, the present framework finds no significant impact of SAAC on GMAU, suggesting that while sensor precision is important, other factors such as DSP, IC, and DAP may have a more substantial influence in the UAE's specific context. Similarly, studies by (Dritsas & Trigka, 2025) and (Maraveas, Loukatos, & Arvanitis, 2025) emphasize the importance of network infrastructure in IoT-based systems for real-time data transmission. In contrast, this framework finds CNI to be an insignificant factor in GMAU, potentially due to specific implementation conditions in the UAE.

As compared with prior researches, the study identifies key areas for optimizing greenhouse gas monitoring. DSP, IC, and DAP are critical factors, while SAAC and CNI have a lower impact. This contributes to existing knowledge by assessing these factors in the UAE's unique setting and providing insights for resource allocation, system integration, and decision-making to enhance environmental monitoring efforts.

## 5. Discussion

An unexpected until now theoretically meaningful finding of this study is the lack of a statistically significant effect of Sensor Accuracy and Calibration (SAAC) and Connectivity and Network Infrastructure (CNI) on the adoption of IoT-based greenhouse gas (GHG) monitoring systems. While prior studies frequently identify these factors as critical technological enablers of IoT adoption (Atzori et al., 2010; Gubbi et al., 2013), their insignificance in the present model can be explained by contextual characteristics specific to the UAE's technological, regulatory, and institutional environment.

### *5.1 Sensor Accuracy and Calibration (SAAC)*

In many emerging or less technologically mature contexts, sensor accuracy and calibration are regarded as major adoption barriers due to inconsistent standards, limited technical expertise, and fragmented maintenance practices (Kumar et al., 2019; Li et al., 2020).

However, in the UAE context, sensor accuracy appears to function as a baseline requirement rather than a differentiating adoption determinant. Large industrial emitters particularly in the oil, gas, and energy sectors that operate under stringent regulatory regimes and internationally recognized compliance standards, such as ISO 14064 and other environmental reporting frameworks.

As a result, organizations tend to procure certified, vendor-managed sensor solutions with standardized calibration protocols embedded within service-level agreements. This institutionalization of accuracy and calibration minimizes performance variability and reduces managerial concern over technical reliability. Consequently, decision-makers are more likely to focus on strategic and organizational factors, including regulatory compliance, perceived usefulness, and organizational readiness, rather than sensor-level technical characteristics.

From a theoretical perspective, this finding aligns with Diffusion of Innovations (DOI) theory, which posits that once an innovation attribute becomes standardized and widely accepted, its influence on adoption decisions diminishes (Rogers, 2003). In this sense, SAAC operates as a hygiene factor which is necessary for operational functionality but insufficient to motivate adoption independently.

*5.2 Connectivity and Network Infrastructure (CNI)*

Similarly, the insignificance of CNI can be attributed to the UAE's highly advanced and reliable digital infrastructure ecosystem. The country has invested extensively in nationwide broadband connectivity, 5G networks, cloud computing platforms, and industrial IoT ecosystems, particularly in strategically important sectors (Al-Fuqaha et al., 2015; Khan et al., 2022). For most organizations included in this study, connectivity is already robust, ubiquitous, and centrally managed, thereby eliminating it as a perceived adoption barrier.

Moreover, many GHG monitoring initiatives in the UAE operate within centralized or hybrid system architectures, where data collection, transmission, and analytics are managed through secure enterprise platforms rather than decentralized or ad hoc networks. In such environments, connectivity challenges are abstracted away from operational users and handled at the organizational or governmental level. As noted by Porter and Heppelmann (2014), when digital infrastructure becomes embedded and invisible to users, it loses salience as an adoption determinant.

Accordingly, adoption decisions are driven less by infrastructural readiness and more by organizational alignment, regulatory pressures, and value realization, which is consistent with the significant effects observed for regulatory compliance and perceived usefulness in the model.

*5.3 Infrastructure Maturity and Centralized Governance*

The findings indicate that the UAE has reached a stage of digital and infrastructural maturity in which foundational technological elements such as sensor accuracy and network connectivity no longer explain variation in adoption behaviour. Instead, IoT adoption for

GHG monitoring is shaped by institutional forces, governance structures, and strategic priorities, reflecting a transition from technology-centric to organization-centric adoption dynamics.

This observation is consistent with prior research suggesting that in digitally advanced environments, innovation adoption is increasingly influenced by organizational capabilities and institutional legitimacy rather than basic technical feasibility (Zhu et al., 2006; Venkatesh et al., 2012). Therefore, this study contributes to the literature by demonstrating that IoT adoption determinants are context-dependent and evolve alongside national digital ecosystems.

*5.4 Theoretical Implications (Addition)*

These results extend Diffusion of Innovations theory by illustrating that the relative importance of technological attributes is contingent upon ecosystem maturity. In advanced digital contexts, adoption decisions shift away from technical characteristics toward organizational readiness and institutional alignment, suggesting the need for DOI-based models to more explicitly account for environmental and governance-level moderators.

*5.5 Practical and Policy Implications*

For policymakers, the findings suggest that sustained investment in standardization, certification, and centralized infrastructure governance has effectively reduced technical adoption barriers. Future policy initiatives should therefore prioritize data interoperability, analytics capability, and cross-organizational integration, rather than further infrastructure expansion (OECD, 2021).

For industry practitioners, the results imply that competitive advantage in IoT-enabled GHG monitoring is more likely to arise from effective data utilization, organizational capabilities, and compliance integration, rather than incremental improvements in sensor precision or network performance.

*5.6 Limitations and Future Research*

Although SAAC and CNI were not significant in this study, future research could examine their roles in small and medium-sized enterprises (SMEs) or in less regulated sectors, where infrastructure maturity and standardization may be lower. Cross-country comparative studies would further help identify the boundary conditions under which technological factors regain explanatory power.

## 6. Conclusion

This study presents the development of a validated framework designed to identify the key factors influencing the effective integration of IoT into the UAE's greenhouse gas (GHG) emission monitoring system. The framework was initially crafted using data from 384 employees at the UAE's Department of Hazard Forecasting, Monitoring, and Control (HFMC). The model's measurement and structural components were rigorously evaluated using SmartPLS software, confirming that the model met fitness standards and was statistically sound.

The novelty of this research lies in its empirical validation of the factors that significantly impact GHG monitoring in the UAE, with specific emphasis on Data Security and Privacy (DSP), Interoperability and Compatibility (IC), and Data Analytics and Processing (DAP). These factors were found to have a substantial effect on the effectiveness of IoT-based monitoring systems. The study highlights the critical role of these factors in driving successful IoT adoption, offering new insights into how they contribute to improving the UAE's GHG monitoring capabilities.

The validated framework developed in this study provides a practical tool for stakeholders, assisting in resource allocation, system integration, and informed decision-making aimed at enhancing environmental monitoring programs. By addressing key barriers and drivers identified through rigorous testing, the framework contributes to advancing the UAE's efforts in reducing GHG emissions and improving environmental sustainability. Furthermore, the findings offer a foundation for future research and policy-making that can support IoT-driven innovation in climate change mitigation efforts globally.

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