Received: 8 November 2025 | Revised: 9 March 2026 | Accepted: 15 April 2026 | Published online: 14 May 2026

RESEARCH ARTICLE

Journal of Computational and Cognitive Engineering
2026, Vol. 00(00) 1–15
DOI: 10.47852/bonviewJCCE62028129

BON VIEW PUBLISHING

An IoT-Based Intelligent Monitoring System for Cargo Loss Detection in FPSO-Tanker Oil Transfer

Habibi Palippui[1,*], Daniel Mohammad Rosyid[2], Silvianita Silvianita[2] and Juswan Sade[1]

[1] *Department of Ocean Engineering, Hasanuddin University, Indonesia*

[2] *Department of Ocean Engineering, Institut Teknologi Sepuluh Nopember, Indonesia*

Abstract: This study presents the development of an Internet of Things-based monitoring system for detecting cargo loss during oil transfer operations between Floating Production Storage and Offloading units and receiving tankers. The proposed system integrates an ESP32S microcontroller, ultrasonic sensors, GPS modules, and a web-based dashboard to enable real-time monitoring and detect anomalies. The system is designed to reduce measurement errors and response delays that may lead to cargo discrepancies during transfer operations. Performance evaluation was conducted using prototype-based simulations to assess the system accuracy, responsiveness, and communication reliability. The results demonstrate high measurement accuracy (≥99.8%), fast response time (~180 ms), low latency (~210 ms), and reliable data transmission with a success rate of 98.7%. The system is also capable of detecting abnormal flow conditions or potential leakage within less than 1 min. Compared with conventional SCADA-based systems, the proposed approach offers improved real-time responsiveness, modularity, and adaptability to dynamic offshore environments. The developed system provides a scalable and flexible platform for maritime monitoring applications and establishes a foundation for the future integration of machine learning techniques to enable predictive and adaptive anomaly detection.

Keywords: IoT, cargo loss detection, intelligent monitoring system, FPSO-tanker offloading, maritime safety

1. Introduction

The offshore oil and gas industry plays a critical role in supporting the global energy demand. A key component of this supply chain is the offloading process, in which crude oil is transferred from Floating Production Storage and Offloading (FPSO) units to receiving tankers [1, 2]. This procedure involves handling large volumes of oil under volatile marine conditions, making it prone to operational and safety risks [3], as shown in Figure 1 [4].

FPSOs are self-contained floating platforms that process, store, and transfer crude oil directly to tankers without relying on subsea pipelines [5]. However, offshore conditions such as unpredictable wave motion, limited operational windows, and inter-vessel drift introduce significant challenges. These factors may lead to discrepancies in the transferred cargo volumes, resulting in potential financial losses and reduced operational efficiency [6].

Several monitoring systems have been developed to address these issues; however, most rely on conventional SCADA-based architectures and single-point sensing, which lack the responsiveness and adaptability required for high-risk marine operations [7]. In contrast, recent advances in the Internet of Things (IoT) offer promising pathways for real-time monitoring, anomaly detection, and predictive maintenance of offshore energy systems [8].

One major advantage of the maritime IoT architecture is its communication flexibility. Technologies such as LoRaWAN, NB-IoT, and 4G/5G cellular and satellite links have been explored to ensure robust long-range data transmission from vessels operating in remote waters [9]. Simultaneously, edge computing paradigms have emerged to reduce latency and ensure operational continuity in situations in which cloud connectivity is intermittent or unavailable [10].

From a hardware perspective, oil and gas environments require durable and precise sensing systems. Ultrasonic sensors, pressure sensors, and flow meters must operate reliably under harsh conditions, including saltwater exposure, vibrations, and extreme temperatures [11]. When combined with real-time GPS tracking and multisensor redundancy, these components enable a more robust and reliable data acquisition.

Additionally, predictive maintenance frameworks, such as Prognostics and Health Management, digital twins, and AI-driven monitoring systems, are gaining increasing attention in offshore industries. These approaches leverage historical data and sensor fusion techniques to anticipate failures, optimize asset lifespans, and support proactive decision-making in critical operations [8, 10].

***Corresponding author:** Habibi Palippui, Department of Ocean Engineering, Hasanuddin University, Indonesia. Email: habibi@unhas.ac.id

Figure 1
FPSO-tanker offloading configuration and risk zones

Recent developments in maritime IoT systems have emphasized the need for intelligent data processing and advanced analytical capabilities in offshore environments. In addition to communication reliability, modern IoT architectures increasingly incorporate distributed intelligence through edge computing and hybrid network systems to support real-time decision-making under dynamic conditions. These developments highlight the importance of integrating sensing, communication, and data analytics into a unified monitoring framework.

Furthermore, data-driven approaches based on machine learning have been widely applied in industrial and maritime monitoring. Techniques such as neural networks, Gaussian Process Regression (GPR), and ensemble learning models have demonstrated strong capabilities in modeling nonlinear system behavior and detecting anomalies in multisensor environments. These methods enable predictive insights by learning from historical data and identifying complex patterns that cannot be captured using conventional threshold-based approaches. In offshore applications, such approaches have been increasingly adopted for predictive maintenance, fault diagnosis, and condition monitoring, demonstrating their potential to improve system reliability and operational safety.

Despite these advancements, modular and integrated prototypes specifically designed for FPSO-tanker offloading scenarios remain lacking. This study addresses this gap by introducing a low-cost IoT-based monitoring system built around ESP32S microcontrollers equipped with redundant ultrasonic sensors, GPS tracking, real-time dashboards, and anomaly detection capabilities. The proposed system emphasizes modularity, operational resilience, and applicability in dynamic offshore environments.

2. Materials and Methods

Design and testing of an integrated digital monitoring system for crude oil transfer from an FPSO to a tanker are presented in this study. The adopted approach enables iterative system design, modular development, and direct performance evaluation under simulated conditions that resemble real offshore environments [12].

Figure 2 illustrates the development of the intelligent monitoring system through successive stages, including requirements analysis, hardware design, software implementation, system integration, and testing.

Each development stage is represented by a distinct color in the flowchart: light blue indicates requirement analysis, yellow indicates hardware design, green indicates software development, purple indicates system integration, and red indicates testing and evaluation. This methodology follows a modular development and simulation-based validation approach, ensuring flexibility and adaptability for future system improvements.

The prototype development process is illustrated in Figure 3, which presents a structured workflow from the conceptual design to the simulation. The process begins with 3D modeling of the tanker system to ensure the proper placement of key components, followed by 3D printing to produce the physical prototype. The assembly stage involved constructing the structure and checking for any mechanical misalignment before installing the ultrasonic sensors and GPS module [12].

Next, the sensors were installed and configured to enable continuous data acquisition, communication with the monitoring dashboard, and automated alarm-setting. Simulated manual water testing was conducted to evaluate the system performance under controlled conditions. The testing verified the sensor communication, system responsiveness, and measurement accuracy, confirming that the system is capable of reliable operation and is ready for deployment in real or scaled operational environments.

As illustrated in Figure 4, the development process begins with a system requirement analysis, in which key monitoring parameters, such as oil tank levels, vessel position, and environmental conditions, are identified. Subsequently, the system enters the initialization phase, which includes the sensor module configuration, baseline data acquisition, and network setup.

The subsequent stages involved real-time data acquisition, transmission to the ESP32S microcontroller, and visualization using a web-based dashboard. The system implements real-time anomaly detection by comparing incoming data with pre-recorded reference values. Prior to deployment, the prototype underwent multiple testing phases, including accuracy validation, communication reliability assessment, and basic cybersecurity evaluation. This iterative and integrated development approach is particularly suitable for IoT-based maritime systems, where synchronization

Figure 2
Prototype engineering methodology flowchart

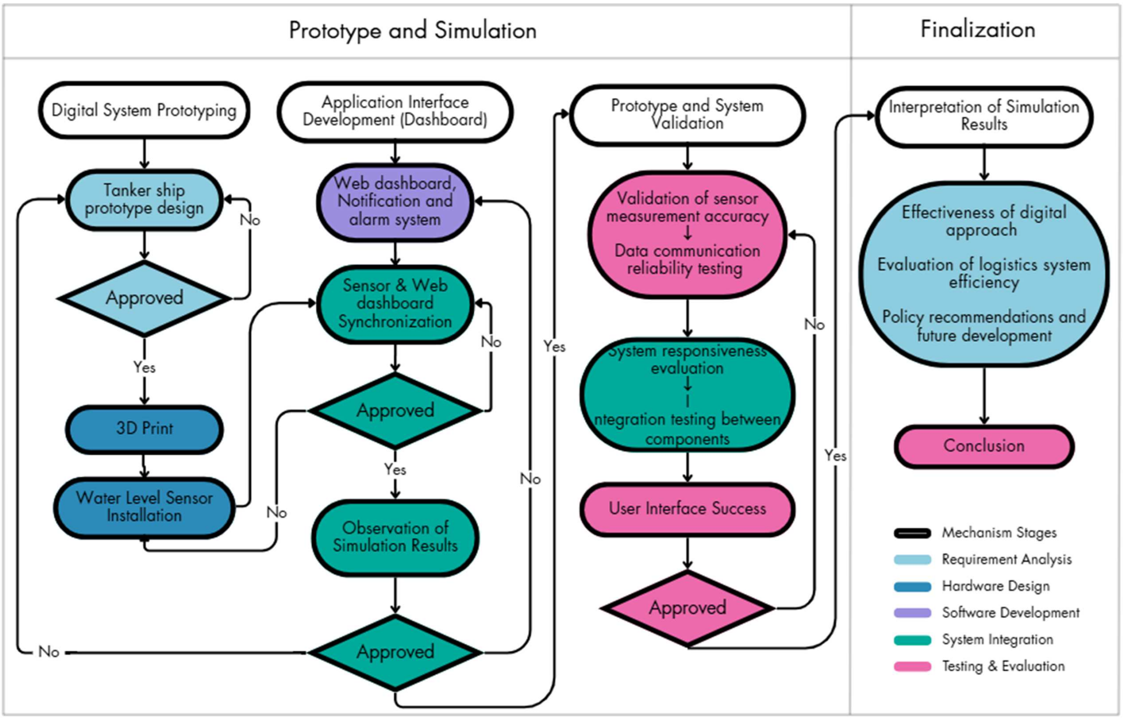
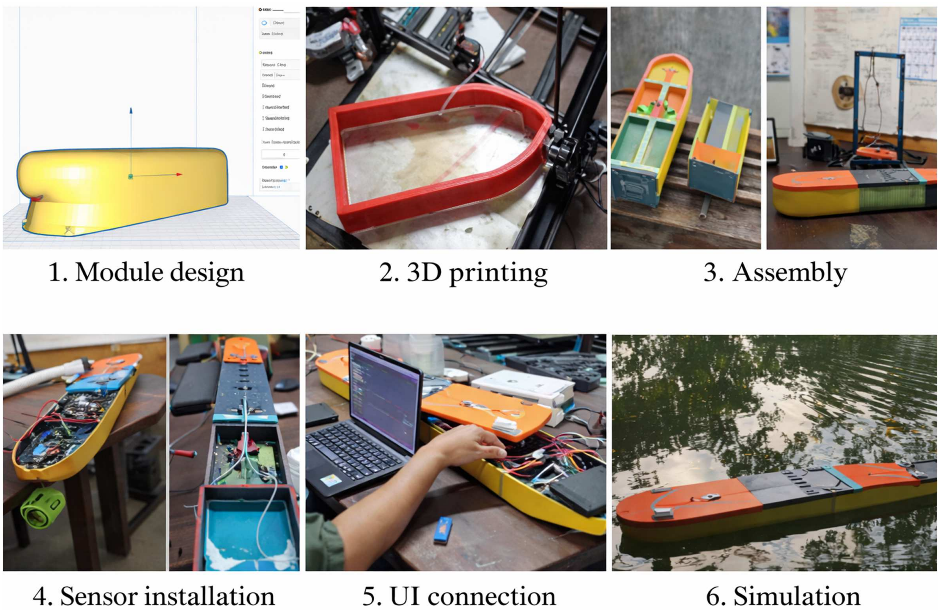


Figure 3
Prototype engineering stages for system development

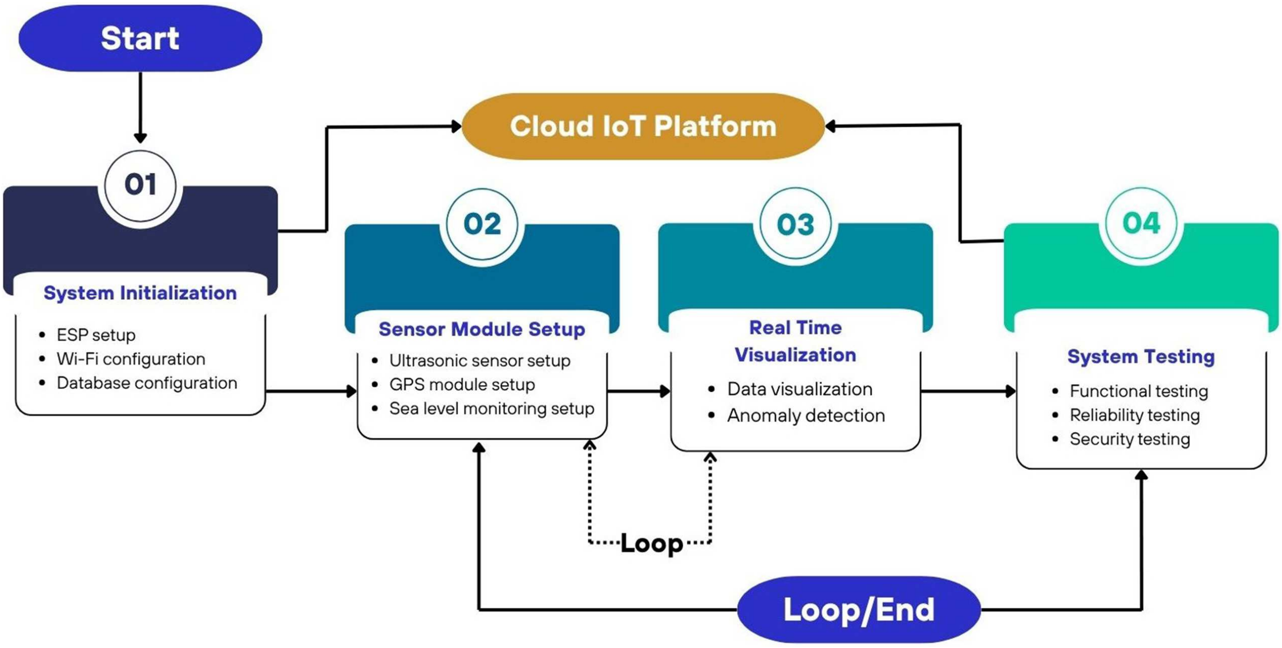


between hardware and software components is essential to ensure reliable, real-time performance and data integrity [13].

The monitoring system was developed using a modular architecture consisting of a sensor assembly, data processing, information transmission, and visualization through a web-based user interface. The ESP32S microcontroller serves as the main processing unit, whereas redundant HC-SR04 ultrasonic sensors are used to measure tank levels in real time [14]. In addition, the NEO-7M GPS module provides position tracking with one-second update intervals. The communication system was designed using a local wireless network with basic data security protocols and was connected to a database that stored historical system activity logs.

Several studies have emphasized the importance of real-time interfaces in supporting risk mitigation and operational decision-making in high-risk offshore environments [15, 16]. To facilitate data visualization and improve decision-making, a web-based interface was developed using HTML, PHP, and JavaScript [17].

Figure 4
Block diagram of the integrated monitoring system



This interface enables operators to monitor real-time data, receive automatic alerts for anomalies, and access historical records for evaluation. The system architecture was based on prior research on IoT-based maritime monitoring and predictive maintenance systems [18]. As illustrated in Figure 5, the dashboard provides a user-friendly interface for visualizing the tank levels, flow rates, and system alerts.

The data collection process was conducted in two forms: real-time measurement of operational parameters using sensors and GPS modules and automatic system logging. The logging mechanism records the sensor data, system events, and performance metrics for further analysis. System testing was performed through simulation-based evaluations, including functional testing, reliability assessments, and basic security testing. Functional testing focused on measurement accuracy, sensor response time, and system performance under varying conditions, whereas reliability testing evaluated the system behavior under extreme scenarios. This evaluation approach is consistent with the methodologies applied in IoT-based maritime monitoring and predictive system validation [19].

The selection of parameters, such as an ideal response time of 180 ms and a data transmission sample size of 10,800 packets, was based on the operational requirements of real-time alert systems in offshore environments. According to prior studies on offshore automation, detection delays exceeding 250 ms may lead to operational lag, indicating that the system's average latency (210 ms) and response time (180 ms) fall within the acceptable industry thresholds [20–22].

Data analysis was conducted using a combination of quantitative and qualitative approaches. The sensor accuracy, data communication latency, and overall system performance were quantitatively evaluated using the following equations [23, 24]:

The accuracy was calculated using the following formula:

$$Accuracy\ (\%) = \left(1 - \frac{|V_{sensor} - V_{actual}|}{V_{actual}}\right) \times 100 \tag{1}$$

V_{sensor} is the volume measured by the sensor, and V_{actual} is the reference (actual) volume based on calibration.

The success rate of transmission was calculated as follows:

$$Success\ Rate\ (\%) = \left(\frac{N_{received}}{N_{sent}}\right) \times 100\% \tag{2}$$

$N_{received}$ is the total number of data packets sent, and N_{sent} is the number of data packets received without errors.

Latency was computed as follows:

$$t_{latency} = (t_{dashboard} - t_{sensor}) \times 100\% \tag{3}$$

$t_{dashboard}$ is the timestamp when the data are recorded at the sensor, and t_{sensor} is the timestamp when the data appear on the dashboard.

The response time was calculated using the following formula:

$$Response\ time = t_{sensor\ detect} - t_{volume\ changed} \tag{4}$$

$t_{sensor\ detect}$ is the time when the sensor reading indicates a change, and $t_{volume\ changed}$ is the time when the volume change occurs.

To complement the mean values, the standard deviation (Std. Dev.) was calculated to assess the variability and consistency of each parameter. A low standard deviation indicates that the sensor readings, response times, and latency values are closely distributed around the mean, confirming the stability and reliability of the system under dynamic testing conditions. This approach followed the standard practices for experimental performance evaluation. The standard deviation was calculated as follows [25]:

$$Std.\ Dev. = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - x_a)^2} \tag{5}$$

Std. Dev. is the standard deviation, n is the number of values, x_a is the sample average, and x_i is the individual value.

Figure 5
Dashboard of sensor data and historical records

Qualitatively, the ease of use of the interface, the effectiveness of data presentation, and the accuracy of the system in responding to anomalous conditions were evaluated [26]. This dual evaluation approach ensures that the system is not only technically robust [27] but also adaptable to operational requirements, in line with approaches reported in recent literature on digital-based maritime systems.

2.1. Anomaly detection algorithm

This study employs a lightweight yet effective anomaly detection mechanism designed to identify potential cargo loss during oil transfer from an FPSO unit to a receiving tanker. The proposed approach is based on a trend deviation method that compares real-time sensor measurements with a predefined baseline that represents normal operating conditions.

Let V_{measured} denote the real-time volume obtained from the ultrasonic sensor readings and V_{baseline} denote the reference volume established during the initialization phase. The deviation between the measured and expected values is defined as

$$D = | V_{\text{measured}} - V_{\text{baseline}} | \tag{6}$$

An anomaly is detected when the deviation exceeds a predefined threshold T:

$$D > T$$

In this study, the threshold was defined as a percentage of the baseline value.

$$T = \alpha \cdot V_{\text{baseline}} \tag{7}$$

where α is a sensitivity parameter empirically set to 0.1(10%). Therefore, any volume reduction greater than 10% of the baseline was classified as a potential anomaly, indicating possible cargo leakage or abnormal transfer conditions.

This formulation provides a mathematically interpretable and reproducible framework for detecting anomalies. This approach can be categorized as a threshold-based statistical monitoring method, in which deviations from the expected operational behavior are used to identify abnormal system states. The rationale behind this approach prioritizes computational efficiency and real-time responsiveness, particularly given the deployment of a resource-constrained microcontroller (ESP32). Instead of employing computationally intensive data-driven models, the system relies on a baseline averaging process derived from the initial sensor readings, followed by continuous deviation monitoring.

Although the method does not incorporate adaptive learning or temporal pattern recognition, it demonstrates high reliability in detecting sudden and critical volume changes during the transfer operations. Furthermore, the developed IoT platform provides a robust data-acquisition infrastructure that supports the future integration of advanced data-driven approaches, such as machine learning models, enabling adaptive and predictive anomaly detection in more complex operational scenarios. This approach shares similarities with statistical process monitoring techniques, in which deviations from expected trends are used as indicators of abnormal system behavior.

2.2. Baseline initialization

The system acquired an initial reading from each of the ultrasonic sensors at the points before the transfer started. These readings were sampled over a short period to eliminate transient vibrations and ensure a stable baseline estimation. The values were averaged to give the baseline (V_{initial}) as a reference for all subsequent measurements. This baseline is important as it becomes the initial point of the cargo, and the system can determine, during transfer, if there are any abnormal changes or just natural variations.

By grounding the monitoring process in real measurements rather than assuming values, the system improves the reliability of anomaly detection. Environmental factors such as vibration, temperature, or minor surface movement can introduce noise into individual readings, and averaging helps to minimize these effects. This simple baseline approach ensures that the system identifies meaningful deviations without being overly sensitive to small fluctuations, thereby providing a practical foundation for real-time monitoring and alarm activation throughout the operation cycle.

2.3. Real-time comparison and threshold logic

During the operation, the system compared the real-time volume readings ($V_{\text{real-time}}$) with the previously established baseline. If the measured value decreases by more than 10% compared with the baseline, the system interprets this as an abnormal deviation, potentially indicating a leak, loss, or other anomaly in the transfer process. This logic follows a straightforward rule:

$$\text{If}\,\frac{V_{\text{real-time}}}{V_{\text{initial}}} < 0.9 \Rightarrow \text{Trigger Anomaly Alert} \tag{8}$$

The 10% threshold was determined empirically based on the initial trial runs and was selected to strike a balance between responsiveness and resilience to minor fluctuations that do not pose operational risks.

2.4. Alert mechanism and response time

When a significant deviation from the normal sensor reading is detected, the system automatically triggers an alert mechanism indicating potential cargo loss. Both visual and audible alarms were activated locally to ensure immediate operator awareness. Simultaneously, anomaly data are transmitted to a centralized web-based dashboard, enabling remote monitoring and rapid response.

This dual-layer alert mechanism ensures that warnings are delivered both locally and remotely, thereby improving the system's reliability and safety. The experimental results indicate that the system achieves an average response time of approximately 180 ms from anomaly detection to alert activation. This rapid response is critical in offshore oil transfer operations, where the early detection of irregularities can significantly reduce environmental and financial risks.

2.5. Sensor calibration procedure

Each ultrasonic sensor was calibrated before use for volume measurement. The calibration process was conducted by comparing the distance readings obtained from the sensors with manual measurements of the liquid depth using a calibrated dipstick and graduated measuring tape. These instruments are commonly used in industrial tank measurements and serve as reliable references for establishing ground-truth data.

To ensure accurate calibration, measurements were performed at predefined volume levels of 10%, 25%, 50%, 75%, and 100% of the tank's capacity. At each level, repeated measurements were performed to minimize random errors and ensure repeatability. The reference volume V_{actual} was determined from the measured liquid height based on the known tank geometry, allowing a direct comparison with the sensor-derived volume estimates. The mean deviation between the sensor readings and reference measurements was consistently maintained within ±1.5 cm, indicating a high level of measurement accuracy suitable for real-time cargo monitoring in dynamic offshore conditions.

2.6. Limitations and future enhancements

Although the current method offers a fast and efficient solution suitable for microcontroller-based platforms, such as the ESP32, it operates on a fixed-threshold mechanism that does not incorporate adaptive learning. This makes the system reactive rather than predictive, limiting its ability to detect more complex or gradual anomalies such as sensor drift, slow leaks, or inconsistent multisensor behavior.

Although effective in identifying sudden volume changes, the algorithm does not adapt over time or analyze temporal or contextual patterns across sensor readings. These constraints highlight the need for more sophisticated techniques in future development, particularly for models that can process historical trends and dynamically adjust to evolving operational contexts in the future. Despite these limitations, the current system serves as a reliable foundation for such extensions by ensuring consistent data acquisition and timely detection of major anomalies.

3. Results

To address the objectives outlined in the introduction, the system was tested through a series of simulations to evaluate its accuracy, response, and usability.

3.1. Tank-level measurement accuracy

This measurement aimed to verify the accuracy and reliability of the tank-level detection system under simulated conditions, ensuring its effectiveness for dynamic fluid monitoring during offshore oil transfer operations [28, 29]. The tank-level accuracy was measured by comparing the results of the HC-SR04 ultrasonic sensor with the actual volume determined using the calibration tank. Data were obtained from six symmetrically installed sensors with readings taken every 500 ms during the operational simulation.

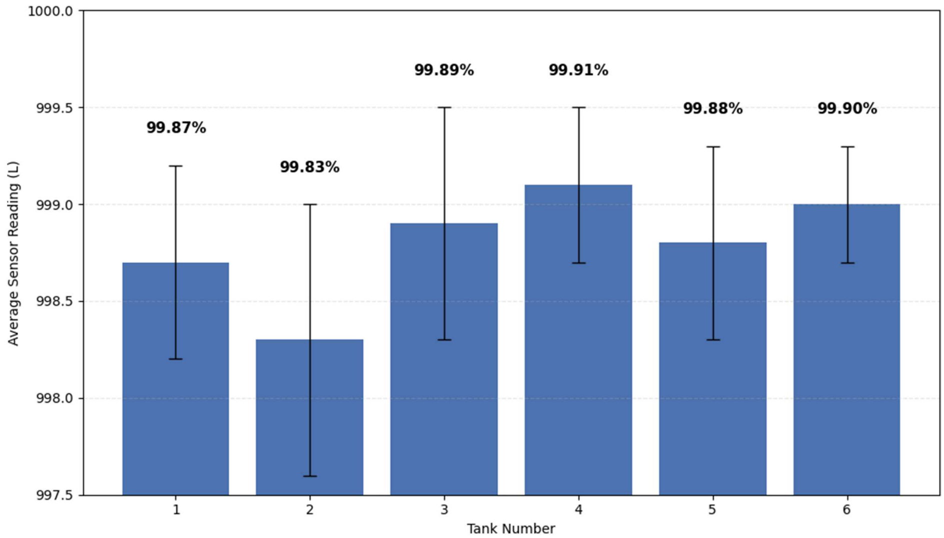
Table 1 presents the accuracy of the ultrasonic sensors in measuring the oil volume at various tank levels, with a deviation margin of less than 0.5%. The use of dual (redundant) sensors allows the system to continue providing valid data even if one of the sensors is disrupted. This is in accordance with the principle of sensor redundancy in critical monitoring systems [30].

The mean accuracy for each tank setting is presented in Figure 6, showing a strong agreement between the measured and reference values. Additionally, all ultrasonic sensors reached

Table 1
Tank volume measurement accuracy

Tank No.	Avg. Sensor Reading (L)	Std. Dev.	Accuracy (%)
1	998.7	0.5	99.87
2	998.3	0.7	99.83
3	998.9	0.6	99.89
4	999.1	0.4	99.91
5	998.8	0.5	99.88
6	999.0	0.3	99.90

Figure 6
Visual comparison of tank-level measurements



an accuracy above 99.8% with low values for standard deviation (<0.7 L) (Table 1 and Figure 6). This demonstrates good concordance between the tanks and that the redundant sensor configuration performs reliably. This consistency in reading indicates the reliability of the system under the test conditions.

3.2. Sensor response time

This measure was aimed at evaluating the speed at which the system could detect changes in the fluid volume, which is critical for a timely response during offshore oil transfers [31]. The response time was measured from the interval between the actual volume change in the simulated tank and the time at which the sensor provided a data update. The experiment was conducted by simulating a rapid increase and decrease in the liquid volume and recording the detection lag time [22].

The results indicate an average response time within the ideal range for real-time monitoring in dynamic environments. This fast response is important to ensure that the system can detect volume deviations instantly and activate an early warning system.

The average response time of the system is summarized in Table 2, which shows the consistency of the system under dynamic testing conditions. The measured response times for different tank samples are shown in Figure 7, indicating a consistent detection speed of the system under dynamic conditions.

Figure 7 illustrates the consistent sensor response times across the different tank samples, with an average of 180 ms; the blue line indicates the average response time (in milliseconds) for each tank, and the gray shaded area represents the minimum and maximum ranges for each tank's response time. This rapid detection is critical for real-time monitoring in dynamic marine environments, where sudden volume changes must be immediately identified to trigger early warnings and prevent cargo discrepancies from occurring.

3.3. Data transmission

The success rate of data transmission was evaluated by calculating the percentage of sensor data packets that were successfully received and stored in the database. The test was conducted for 3 h of simulation with a sending interval of 1 s. Of the more than 10,000 data packets sent, 98.7% were successfully received without any data loss. These results indicate a stable and efficient wireless communication system that is consistent with the characteristics of maritime IoT systems [32].

As shown in Table 3, the system maintained a transmission success rate of above 98%, confirming stable communication. The consistency in the transmission success rate across different tank scenarios is shown in Figure 8, demonstrating the system reliability of wireless data transfer during oil offloading simulations.

The results in Table 3 and Figure 8 show that more than 98% of the data packets were successfully transmitted across all simulation scenarios. This confirms the reliability of the

Table 2
Data transmission and execution response times of the monitoring system

Tank No.	Average	Std. Dev.	Min	Max
1	176.57	6.29	163.87	187.03
2	176.59	5.48	164.01	185.45
3	182.23	5.95	171.36	191.96
4	180.92	4.98	171.38	189.09
5	184.36	5.37	177.18	194.44
6	185.81	6.42	175.87	198.99

Table 3
Data transmission success rate in test conditions

Tank No.	Packet sent	Packet received	Success (%)
1	10800	10657	98.68
2	10800	10701	99.08
3	10800	10652	98.63
4	10800	10732	99.37
5	10800	10658	98.69
6	10800	10686	98.94

Figure 7
System response time and data transmission performance

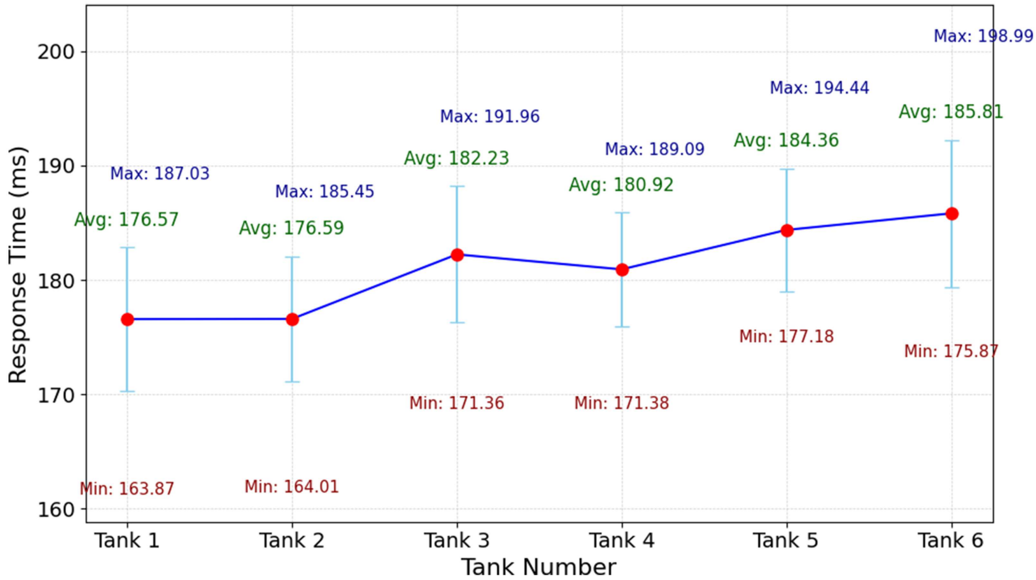
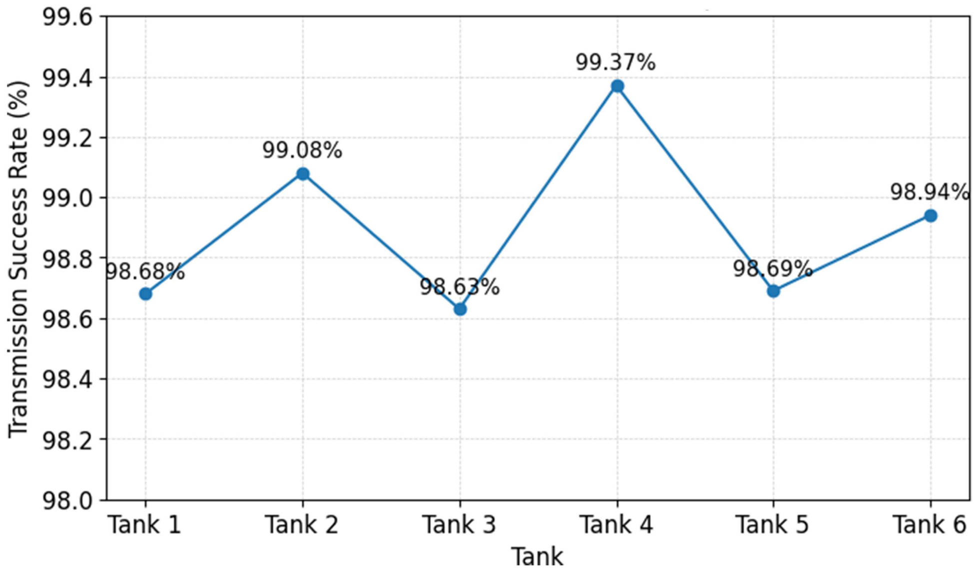


Figure 8
Data transmission success rate under test conditions



wireless communication architecture, which is essential for offshore operations that are prone to signal interference.

3.4. Communication latency

Latency was measured as the time elapsed from sensor data acquisition to its display on the user interface dashboard. As presented in Table 4, the sensor-to-dashboard latency under varying network conditions showed an average value of approximately 210 ms, satisfying the real-time monitoring requirements.

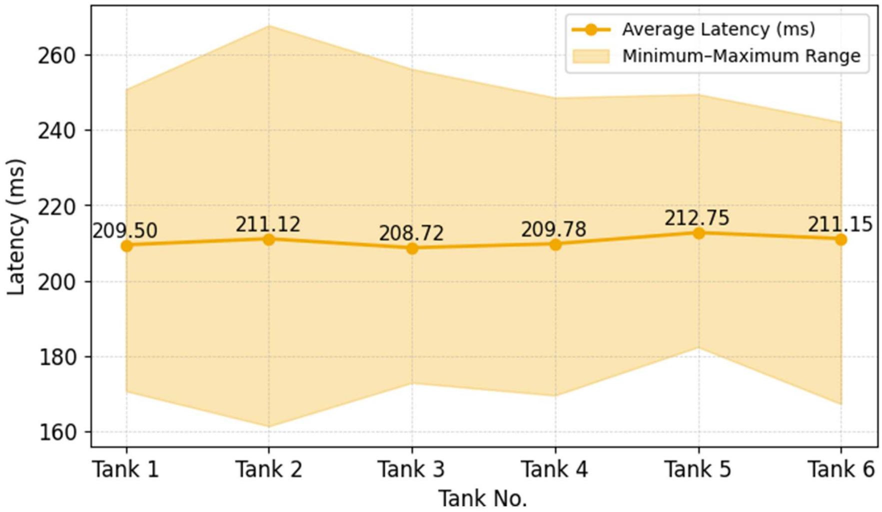
The latency values were relatively low, indicating that the system could deliver near real-time data with minimal delays. The latency analysis results are presented in Figure 9, which demonstrates consistent system responsiveness across different operating conditions.

Table 4
Sensor-to-dashboard latency under varying network conditions

Tank No.	Average (ms)	Std. Dev.	Minimum (ms)	Maximum (ms)
1	209.505	14.019	170.703	250.802
2	211.120	14.393	161.381	267.791
3	208.721	15.362	172.925	256.183
4	209.784	15.280	169.546	248.600
5	212.750	14.187	182.386	249.485
6	211.151	14.474	167.271	242.134

The dark yellow line shows the average latency per tank, and the light yellow shaded area illustrates the range from the

Figure 9
Sensor-to-dashboard latency under varying network conditions



minimum to the average value, highlighting the variation in latency. Figure 9 confirms that this low latency ensures that the sensor data appear on the dashboard almost instantly, allowing operators to make timely and informed decisions.

3.5. Anomaly detection time latency

Automatic anomaly detection systems rely on algorithms that compare historical and current data trends. The detection time was calculated from the emergence of the deviation value until the system issued a notification to the user. The test results showed that the system could detect anomalies in less than 1 min (average of 0.9 min), thus meeting the industry standard for early detection in volatile fluid-transfer systems.

The detection algorithm uses a trend deviation method to compare the baseline historical sensor data with the real-time values to identify abrupt changes in the flow rate or valve status. This fast detection is crucial for reducing logistic loss because it shortens the response time to leaks or transfer-volume mismatches. Table 5 shows the response time of the system in detecting anomalies, such as valve leaks or unauthorized changes in the flow rate.

Figure 10 shows the anomaly detection time for each tank sample, confirming the system's capability to issue alerts in less than 1 min, which is crucial for minimizing the cargo loss risk during oil offloading operations.

Table 5
Anomaly detection speed under simulated flow irregularities

Tank No.	Average (ms)	Std. Dev.	Minimum (ms)
1	0.89	0.08	0.75
2	0.96	0.09	0.76
3	0.92	0.07	0.80
4	0.94	0.06	0.79
5	0.86	0.10	0.78
6	0.94	0.09	0.77

In addition, Figure 10 shows that the system can detect anomalies in less than 1 min. This rapid detection is crucial for preventing major losses owing to leaks or undetected volume deviations.

3.6. User interface usability testing

The usability of the user interface was assessed by testing ten simulated operator participants with marine engineering experience. Each participant performed monitoring tasks and responded to the system-generated alerts in real time. The success rate was measured using three overarching factors: speed of information retrieval, clarity in the presentation of data, and ease of navigation around the interface. These values represent the critical requirements of offshore operations, which are necessary to enable fast decisions.

The usability of the system was evaluated through tests involving 10 participants with marine or engineering backgrounds. Each participant performed monitoring tasks and responded to the system-generated alerts in real time. The evaluation focused on three key aspects: the information retrieval speed, clarity of data presentation, and ease of navigation. The results indicate a high usability score, with an average success rate of 95.2%, as shown in Table 6. This demonstrates that the system interface effectively supports rapid and accurate operator responses in simulated alert conditions.

Figure 11 presents the dashboard access speed distribution across all respondents, confirming consistently high responsiveness during system alerts. These results demonstrate the intuitive nature of the interface and its ability to support time-sensitive operational decisions, particularly in maritime transfer scenarios, where delays can lead to safety and financial risks.

Although a high average usability score of 95.2% was achieved, the evaluation was limited by the small sample size (n = 10). All the participants completed the scenario-based tasks. However, this result cannot be statistically generalized to a wider operational context. Based on the sample size, this corresponds to an approximate 95% confidence interval of 87.3–100%. This highlights the need to validate system reliability using a larger and more diverse user population, particularly under realistic offshore conditions, where operator fatigue and stress levels may affect performance.

Figure 10
Anomaly detection response time under simulated flow conditions

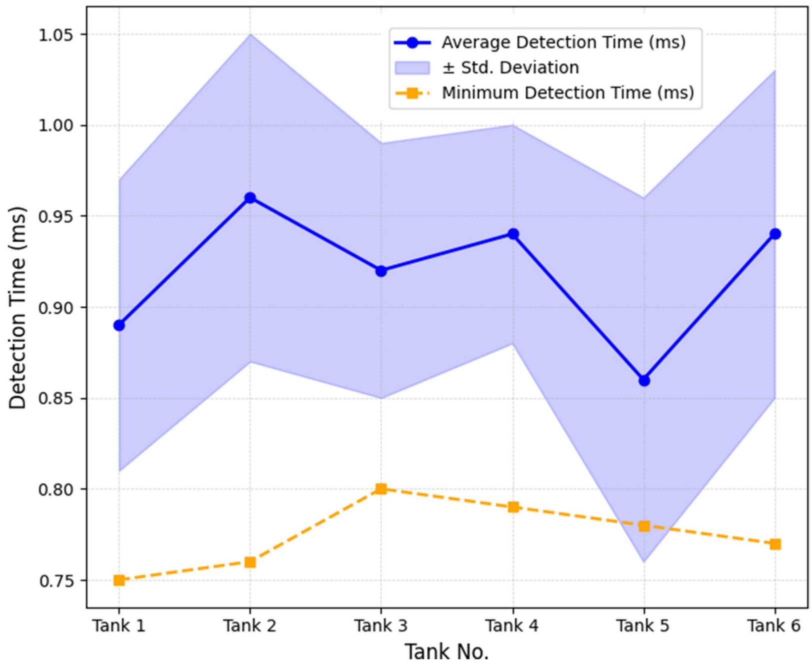
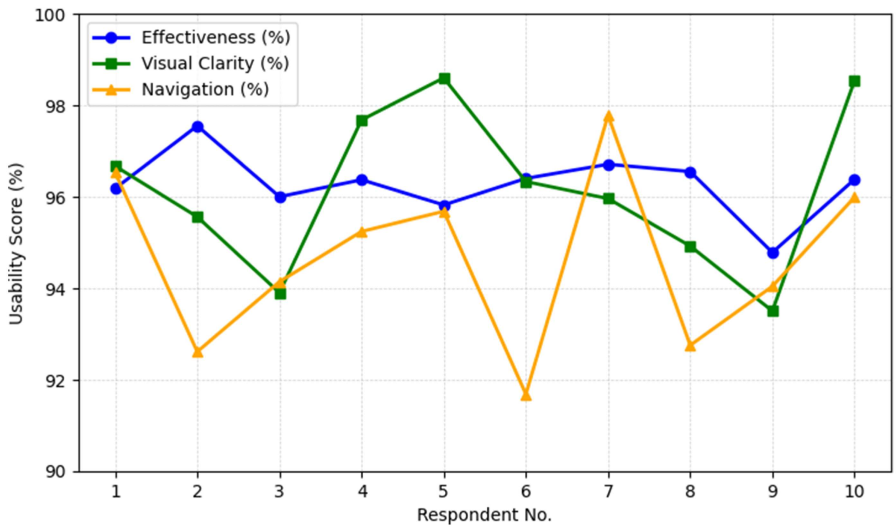


Table 6
Dashboard usability evaluation based on key interface criteria

Respondent	Effectiveness (%)	Visual Clarity (%)	Navigation (%)
1	96.18	96.67	96.53
2	97.55	95.56	92.61
3	96.00	93.90	94.14
4	96.37	97.68	95.24
5	95.82	98.60	95.68
6	96.40	96.33	91.68
7	96.71	95.96	97.78
8	96.55	94.92	92.75
9	94.78	93.50	94.04
10	96.38	98.54	95.99

Figure 11
Visual of dashboard usability evaluation based on key interface criteria



4. Analysis and Discussion

The results of this study demonstrate that the developed digital monitoring system effectively simulates the offloading process from an FPSO to a tanker. The high accuracy of the sensor readings (average of >99%) indicates that the system is suitable for use in dynamic marine environments. It successfully integrates key features, such as redundant ultrasonic sensors, real-time GPS tracking, and a user-friendly web-based interface.

Compared with previous solutions, this system delivers improved integration of hardware and software components, rapid anomaly detection (<1 min), and stable wireless data communication (>98% success rate). These technical enhancements have significantly reduced the risk of cargo loss. In addition, the modular design of the system enables scalable deployment and simplified maintenance, which is an advantage over rigid SCADA-based systems. These strengths are particularly valuable in offshore operations, which are prone to measurement errors and delayed responses. Conventional SCADA-based systems, which are still widely adopted, are often rigid, centralized, and less adaptable to sensor misalignment and communication delays in offshore environments [33]. This underscores the importance of modular and intelligent systems, such as those proposed in this study.

For example, the Offloading Monitoring Telemetry System developed by Star Controls relies on wireless telemetry and automated safety controls to secure the transfer process (Star Controls n.d.). However, it lacks comprehensive real-time data visualization and modular IoT-based architecture, which are central to the proposed system's capability.

Another example is Petrobras, which, together with Atmos International, implemented a mass balance and statistical leakage detection system during offloading operations [34]. Although effective in detecting leakages, this approach does not include anomaly detection features for vessel drift, valve failures, or real-time sensor validation.

Faststream Technologies has introduced an IoT-based oil-monitoring system that tracks the oil volume in tankers and enables leakage detection through periodic volume readings [35, 36]. Although it supports automated notifications, the system is not specifically designed for FPSO-tanker offloading operations and lacks real-time dashboards and sensor redundancy, which are essential for critical maritime logistics [37].

The threshold-based anomaly detection algorithm demonstrated consistent performance in identifying significant volume deviations, particularly when the real-time sensor readings fell below 90% of the initial baseline readings. This finding supports the practical utility of the algorithm in flagging abrupt losses during cargo transfer operations. Although relatively simple, this approach offers a reliable framework for real-time monitoring and lays the groundwork for the future integration of predictive modeling techniques, such as machine learning, to improve anomaly classification and reduce false alarms.

Therefore, this study presents a novel modular solution based on an ESP32S microcontroller that integrates hardware components (ultrasonic sensors and GPS) with software elements (web-based dashboard and automated anomaly detection). The system was specifically tailored to the dynamic and high-risk contexts of FPSO offloading operations. Its modularity also allows future upgrades, including the incorporation of machine learning algorithms to enable adaptive anomaly detection under varying operational conditions [37]. This system represents the first field-tested modular solution explicitly developed for FPSO-tanker cargo monitoring.

4.1. Performance evaluation metrics and limitations

Although the prototype results demonstrated high accuracy and fast response times, a more comprehensive performance evaluation is required to align with the standard practices in anomaly detection and regression-based monitoring. In addition to reporting the average accuracy and latency, this study adopted standard evaluation metrics to provide a more rigorous analytical framework. For volume estimation, the mean absolute error (MAE) and root mean square error (RMSE) are defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{10}$$

where y_i represents the reference (actual) volume obtained during calibration and $\hat{y}_i$ represents the volume measured by the sensor system. These metrics provide a more reliable assessment of the estimation error than a single aggregate accuracy value. For anomaly detection, classification-based evaluation metrics, such as precision, recall, and F1-score, are commonly used to quantify the detection performance.

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

$$F1\text{-}score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{13}$$

These metrics allow for a more detailed analysis of false alarms and missed detections, which are critical in safety-sensitive offshore operations. However, owing to the controlled prototype environment and limited anomaly scenarios, a complete confusion matrix was not systematically recorded during testing. Consequently, false positives and false negatives could not be explicitly quantified. This limitation is acknowledged as a constraint of this study. Future work will focus on collecting extended datasets under real offshore conditions, enabling a statistically robust evaluation using these metrics and facilitating more meaningful comparisons with existing monitoring systems. The inclusion of these performance indicators strengthens the transition from prototype validation to scalable and operational deployment.

4.2. System limitations and scalability considerations

Several limitations of the proposed system should be acknowledged before considering its full-scale deployment. First, experimental validation was conducted under controlled simulation conditions. In real offshore environments, factors such as wave-induced motion, vessel vibration, temperature fluctuations, and humidity can significantly affect sensor accuracy and communication reliability. These environmental conditions were not fully incorporated in the present study and may influence the system performance in actual operations.

In addition, the usability evaluation involved a relatively small sample size (n = 10), which may limit the generalizability of our results. Although the reported usability success rate of

95.2% indicates positive system performance, the limited number of participants may not fully represent the broader operational conditions and user variability. To provide a more statistically meaningful interpretation, future studies should incorporate larger sample sizes and apply confidence interval analyses to better quantify the uncertainty in usability outcomes. Expanding the evaluation to include diverse operational scenarios and user profiles would further enhance the robustness and reliability of system assessment.

Second, the anomaly scenarios evaluated in this study were relatively simplified, including valve malfunctions and sudden volume drop. Under real-world conditions, anomalies may develop gradually, such as slow leakage, sensor drift, or complex interactions among multiple sensors. The effectiveness of the current approach in detecting such complex and evolving anomaly patterns remains to be investigated further.

Third, scalability is an important challenge. The current prototype utilizes six sensors; however, a full-scale FPSO system may require the deployment of dozens to hundreds of sensors to ensure its safety. Scaling the system can introduce issues related to data throughput, synchronization, and latency. Although the ESP32S microcontroller performs efficiently in small-scale applications, it may require integration with more advanced architectures, such as edge computing or distributed processing, to maintain its performance in large-scale implementations.

Finally, cybersecurity requires further attention. Although basic communication security mechanisms have been implemented, the system has not been extensively evaluated against potential threats, such as data spoofing, signal jamming, and unauthorized access. Given the critical nature of offshore oil transfer operations, strengthening the system resilience against such risks is essential for future development.

4.3. Future work: Toward machine learning-enhanced anomaly detection

Future research will focus on enhancing the intelligence and adaptability of the proposed monitoring systems. Although the current threshold-based approach provides reliable detection of abrupt anomalies, it remains limited in capturing gradual or complex patterns influenced by environmental conditions, such as wave motion, turbulence, and sensor drift.

To address these limitations, future studies should explore the integration of machine learning techniques, including neural networks, GPR, and ensemble models [38–42]. These approaches have demonstrated strong capabilities in modeling nonlinear system behavior and capturing complex patterns in multisensor environments. GPR provides probabilistic predictions with uncertainty quantification, whereas neural networks and ensemble methods enable robust anomaly classification based on historical data patterns.

By incorporating adaptive and data-driven models, the system can evolve into a more intelligent and proactive monitoring solution for offshore oil transfer operations. This progression aligns with recent developments in predictive analytics and intelligent maritime monitoring systems [39, 40].

4.4. Intelligent monitoring and machine learning perspective

The proposed system employs a threshold-based anomaly detection mechanism that prioritizes real-time responsiveness and computational efficiency. Although effective for detecting abrupt volume deviations, this approach remains reactive and limited in capturing the complex nonlinear patterns that may arise during FPSO-tanker transfer operations. In this context, the developed IoT platform can be considered not only a monitoring system but also a data-acquisition infrastructure that supports the integration of advanced computational intelligence methods.

Recent studies have demonstrated the effectiveness of machine learning approaches, such as neural networks, GPR, and ensemble models, in modeling nonlinear behaviors and detecting anomalies in industrial monitoring systems. These methods enable predictive and adaptive anomaly detection by learning from multisensor data and identifying subtle patterns beyond fixed thresholds. Therefore, integrating machine learning into the proposed system represents a logical progression toward more intelligent monitoring, improved detection accuracy, reduced false alarms, and enhanced decision-making reliability in offshore oil transfer operations.

5. Conclusions

This study presents the development and validation of an IoT-based monitoring system designed to detect cargo loss during FPSO-to-tanker oil transfer operations. The proposed system integrates ultrasonic sensors, GPS modules, and a web-based dashboard to enable real-time monitoring and detect anomalies. The results demonstrate high measurement accuracy, reliable communication performance, and fast response times, confirming the effectiveness of the system in dynamic offshore environments.

The integration of sensor redundancy, real-time visualization, and automated anomaly detection enhances operational reliability and supports timely decision-making. These features contribute to reducing cargo discrepancies and improving the safety and efficiency of offshore oil transfer operations. In addition, modular system architecture enables scalability and adaptability for broader maritime applications.

This study contributes to the advancement of digital transformation in maritime systems by demonstrating the feasibility of IoT-based intelligent monitoring solutions. The developed platform also serves as a foundation for the future integration of data-driven and machine learning approaches.

Future research should focus on full-scale implementation under real offshore conditions and the integration of advanced machine learning models to enable adaptive and predictive anomaly detection. These developments are expected to improve system intelligence, reduce false alarms, and enhance operational decision-making in complex environments.

5.1. Practical implications

The findings of this study highlight that a well-structured and user-centered digital monitoring system can significantly reduce cargo losses during FPSO-to-tanker transfer operations. The integration of real-time monitoring, anomaly detection, and user-friendly interfaces enables more effective supervision of transfer processes under dynamic, offshore conditions. However, the successful implementation of such systems depends not only on technological capability but also on the readiness of operational personnel.

To ensure effective utilization, structured training programs are required for operators, engineers, and offshore workers. These programs should emphasize practical scenario-based training to enhance users' ability to interpret system outputs and respond appropriately to real-time alerts. Strengthening human-system interactions is essential to maximize the operational benefits of digital monitoring technologies.

Furthermore, the system demonstrates a strong potential for scalability beyond the tested prototype, including applications in broader offshore operations and engineering education. The use of IoT-based dashboards and sensor-driven simulations can support experiential learning, allowing future engineers to develop competencies in system integration, monitoring, and fault diagnosis. This aligns with the ongoing transition toward digitalization in maritime logistics and offshore engineering.

At the institutional level, successful adoption requires adequate infrastructure, continuous innovation support, and integration of digital monitoring systems into operational standards. With proper implementation, modular and intelligent monitoring technologies can transition from experimental prototypes to practical deployable solutions capable of addressing real-world challenges in offshore oil transfer operations.

Acknowledgments

The authors would like to express their sincere appreciation to their colleagues and collaborators from the Institut Teknologi Sepuluh Nopember (ITS) and Universitas Hasanuddin (Unhas) for their continuous support throughout this study. Special acknowledgment was extended to the Offshore Production and Underwater Work Research Laboratory for its technical guidance, resources, and contributions, which played a significant role in the successful completion of this study.

Funding Support

This research was funded by the Indonesian Education Scholarship (BPI) under Kementerian Riset Teknologi Dan Pendidikan Tinggi Republik Indonesia and Kementerian Keuangan Republik Indonesia, Grant number: BPI No. 202209091836.

Ethical Statement

This noninvasive usability study involved voluntary participants from marine or engineering backgrounds, all of whom provided informed consent. No personal or sensitive data were collected, and all data were anonymized and analyzed in aggregate form. The study was reviewed and approved by the Ethical Review Committee of the Faculty of Public Health, Universitas Hasanuddin (Approval No. 1007/UN4.14.1/TP.01.02/2026), Ministry of Education, Culture, Research, and Technology, Republic of Indonesia, in accordance with institutional ethical guidelines and the Declaration of Helsinki.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Habibi Palippui: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Funding acquisition. **Daniel Mohammad Rosyid:** Conceptualization, Resources, Writing – review & editing, Supervision, Project administration. **Silvianita Silvianita:** Methodology, Validation, Formal analysis, Writing – review & editing. **Juswan Sade:** Resources, Writing – review & editing.

References

[1] Palippui, H., Rosyid, D. M., Silvianita, & Sade, J. (2025). Stakeholder engagement based moral hazard analysis model in FPSO-tanker oil transfer. *Emerging Science Journal*, *9*(5), 2674–2686. https://doi.org/10.28991/ESJ-2025-09-05-022

[2] Gaidai, O., Cao, Y., Xu, X., & Xing, Y. (2023). Offloading operation bivariate extreme response statistics for FPSO vessel. *Scientific Reports*, *13*(1), 4695. https://doi.org/10.1038/s41598-023-31533-8

[3] Gaidai, O., Cao, Y., Ashraf, A., Sheng, J., Zhu, Y., & Liu, Z. (2024). FPSO/LNG hawser system lifetime assessment by Gaidai multivariate risk assessment method. *Energy Informatics*, *7*(1), 51. https://doi.org/10.1186/s42162-024-00350-2

[4] Zulqarnain, M. (2015). Deepwater Gulf of Mexico oil spill scenarios development and their associated risk assessment. *Doctoral Dissertation*. Louisiana State University.

[5] França, J. E. M., Hollnagel, E., & Praetorius, G. (2022). Analysing the interactions and complexities of the operations in the production area of an FPSO platform using the functional resonance analysis method (FRAM). *Arabian Journal of Geosciences*, *15*(7), 573. https://doi.org/10.1007/s12517-022-09801-0

[6] Costas, R., Figuero, A., Pena, E., Sande, J., & Rosa-Santos, P. (2022). Integrated approach to assess resonance between basin eigenmodes and moored ship motions with wavelet transform analysis and proposal of operational thresholds. *Ocean Engineering*, *247*, 110678. https://doi.org/10.1016/j.oceaneng.2022.110678

[7] Asgher, M. N., & Iqbal, M. T. (2023). Development of a low-cost, open-source LoRA-based SCADA system for remote monitoring of a hybrid power system for an offshore aquaculture site in Newfoundland. *European Journal of Electrical Engineering and Computer Science*, *7*(6), 65–73. https://doi.org/10.24018/ejece.2023.7.6.589

[8] Zhou, X., Tian, Y., Qin, Y., Charitidis, C. A., Milickovic, T. K., & Termine, S. (2025). An advanced structural health monitoring IoT platform for offshore wind turbine blades. *Manufacturing Review*, *12*, 12. https://doi.org/10.1051/mfreview/2025008

[9] Feng, W., Chen, Y., Li, J., Wang, Y., & Quek, T. Q. S. (2022). Guest editorial: Maritime communications in 5G and beyond networks. *China Communications*, *19*(9), iii–v. https://doi.org/10.23919/jcc.2022.9900230

[10] Jung, S., Jeong, S., Kang, J., & Kang, J. (2023). Marine IoT systems with space–air–sea integrated networks: Hybrid LEO and UAV edge computing. *IEEE Internet of Things Journal*, *10*(23), 20498–20510. https://doi.org/10.1109/jiot.2023.3287196

[11] Johny, J., Amos, S., & Prabhu, R. (2021). Optical fibre-based sensors for oil and gas applications. *Sensors*, *21*(18), 6047. https://doi.org/10.3390/s21186047

[12] Singh, N., Jadhav, S. K., Gaikwad, K., & Haragapure, P. (2025). Tank simulator. *International Scientific Journal of Engineering and Management*, *4*(5), 1–6. https://doi.org/10.55041/isjem03952

[13] Hiekata, K., Wanaka, S., Mitsuyuki, T., Ueno, R., Wada, R., & Moser, B. (2021). Systems analysis for deployment of internet of things (IoT) in the maritime industry. *Journal of Marine Science and Technology*, *26*(2), 459–469. https://doi.org/10.1007/s00773-020-00750-5

[14] Prayetno, E., Nadapdap, T., Susanti, A. S., & Miranda, D. (2021). PLTD engine tank oil volume monitoring system using HC-SR04 ultrasonic sensor based on Internet of Things (IoT). *International Journal of Electrical, Energy and Power System Engineering*, *4*(1), 134–138. https://www.ijeepse.ejournal.unri.ac.id

[15] Mohd Thani, N., Mustapa Kamal, S. M., Taip, F. S., Sulaiman, A., Omar, R., & Wondi, M. H. (2022). Risk assessment of subcritical water hydrolysis (SWH) system for sugar recovery using failure modes and effects analysis (FMEA) methods. *Sains Malaysiana*, *51*(10), 3333–3345. https://doi.org/10.17576/jsm-2022-5110-18

[16] Silvianita, S., Jamaluddin, F. N., Dhanistha, W. L., Suntoyo, S., Satrio, D., & Wahyudi. (2024). Fuzzy logic approach to risk management and control for safe work in jacket structure load out process. *International Review of Automatic Control*, *17*(4), 157–164. https://doi.org/10.15866/ireaco.v17i4.25435

[17] Silvianita, S., Rahmadhan, N. D. A., & Satrio, D. (2025). Risk assessment of project delay analysis on FPSO conversion. *International Journal on Engineering Applications*, *13*(1), 92–101. https://doi.org/10.15866/irea.v13i1.25185

[18] Kushwaha, A., & Gupta, S. (2024). Full stack web development. *International Journal of Scientific Research in Engineering and Management*, *8*(10), 1–6. https://doi.org/10.55041/IJSREM37848

[19] Kalafatelis, A. S., Nomikos, N., Giannopoulos, A., Alexandridis, G., Karditsa, A., & Trakadas, P. (2025). Towards predictive maintenance in the maritime industry: A component-based overview. *Journal of Marine Science and Engineering*, *13*(3), 425. https://doi.org/10.3390/jmse13030425

[20] Noto, S., Gharbaoui, M., Falcitelli, M., Martini, B., Castoldi, P., & Pagano, P. (2023). Experimental evaluation of an IoT-based platform for maritime transport services. *Applied System Innovation*, *6*(3), 58. https://doi.org/10.3390/asi6030058

[21] Martinez, S., Godumagadda, A., Pandey, B., & Malliganuru, N. (2025). Optimizing operational processes and reducing equipment failure through a real time alerting platform. In *SPE/IADC International Drilling Conference and Exhibition*, (SPE-223809-MS). https://doi.org/10.2118/223809-MS

[22] Sayed, R. A. F., Hashim, S. M., Shahin, E. S., & Abd-Elmaksoud, M. H. (2020). Effective use of real-time remote monitoring system in offshore oil wells optimization, case study from Gulf of Suez-July field. In *Offshore Technology Conference*, (OTC-30610-MS). https://doi.org/10.4043/30610-MS

[23] Zeng, Y. (2025). Integration and performance evaluation of embedded sensors in mechatronics systems. *International Journal of High-Speed Electronics and Systems. Advance online publication*. https://doi.org/10.1142/s0129156425406679

[24] Alruwaili, O., Yousef, A., & Armghan, A. (2024). Monitoring the transmission of data from wearable sensors using probabilistic transfer learning. *IEEE Access*, *12*, 97460–97475. https://doi.org/10.1109/access.2024.3428444

[25] Astolfi, M., Rispoli, G., Gherardi, S., Zonta, G., & Malagù, C. (2023). Reproducibility and repeatability tests on (SnTiNb)O2 sensors in detecting ppm-concentrations of CO and up to 40% of humidity: A statistical approach. *Sensors*, *23*(4), 1983. https://doi.org/10.3390/s23041983

[26] Madandola, O. O., Bjarnadottir, R. I., Yao, Y., Ansell, M., dos Santos, F., Cho, H., …, & Keenan, G. M. (2024). The relationship between electronic health records user interface features and data quality of patient clinical information: An integrative review. *Journal of the American Medical Informatics Association*, *31*(1), 240–255. https://doi.org/10.1093/jamia/ocad188

[27] Spandonidis, C., Tzioridis, Z., Petsa, A., & Charanas, N. (2025). Maritime operational intelligence: AR-IoT synergies for energy efficiency and emissions control. *Sustainability*, *17*(17), 7982. https://doi.org/10.3390/su17177982

[28] Pangione, L., Burroughes, G., & Skilton, R. (2021). Variational AutoEncoder to identify anomalous data in robots. *Robotics*, *10*(3), 93. https://doi.org/10.3390/robotics10030093

[29] Li, P., Zhang, N., & Yang, L. (2022). Oil test liquid level monitoring system based on the IoT. In *2022 4th International Conference on Intelligent Control, Measurement and Signal Processing*, 429–433. https://doi.org/10.1109/ICMSP55950.2022.9859197

[30] Gerken, E., & König, A. (2025). Enhancing reliability in redundant homogeneous sensor arrays with Self-X and multidimensional mapping. *Sensors*, *25*(13), 3841. https://doi.org/10.3390/s25133841

[31] Travagnin, M. (2020). *Cold atom interferometry for inertial navigation sensors: Technology assessment: Space and defence applications* (JRC technical reports). European Union. https://publications.jrc.ec.europa.eu/repository/handle/JRC122785

[32] Chen, T.-C., Alizadeh, S. M., Albahar, M. A., Thanoon, M., Alammari, A., Guerrero, J. W. G., …, & Eftekhari-Zadeh, E. (2023). Introducing the effective features using the particle swarm optimization algorithm to increase accuracy in determining the volume percentages of three-phase flows. *Processes*, *11*(1), 236. https://doi.org/10.3390/pr11010236

[33] Liu, S., Zhu, L., Huang, F., Hassan, A., Wang, D., & He, Y. (2024). A survey on air-to-sea integrated maritime internet of things: Enabling technologies, applications, and future challenges. *Journal of Marine Science and Engineering*, *12*(1), 11. https://doi.org/10.3390/jmse12010011

[34] Navarro-Díaz, A., Delgado-Aguiñaga, J. A., Santos-Ruiz, I., & Sánchez-Torres, J. D. (2024). Leak diagnosis in branched pipeline systems based on a robust differentiation scheme. *IEEE Access*, *12*, 62162–62176. https://doi.org/10.1109/access.2024.3393976

[35] Ramzey, H., Badawy, M., Elhosseini, M., & Elbaset, A. A. (2023). I^{2}OT-EC: A framework for smart real-time monitoring and controlling crude oil production exploiting IIOT and edge computing. *Energies*, *16*(4), 2023. https://doi.org/10.3390/en16042023

[36] Ahmed, S., le Mouël, F., Stouls, N., & Kouyi, G. L. (2023). Development and analysis of a distributed leak detection and localisation system for crude oil pipelines. *Sensors*, *23*(9), 4298. https://doi.org/10.3390/s23094298

[37] Kim, D., Antariksa, G., Handayani, M. P., Lee, S., & Lee, J. (2021). Explainable anomaly detection framework for maritime main engine sensor data. *Sensors*, *21*(15), 5200. https://doi.org/10.3390/s21155200

[38] Jin, B., Xu, X., & Zhang, Y. (2025). Peanut oil price change forecasts through the neural network. *Foresight*, *27*(3), 595–612. https://doi.org/10.1108/FS-01-2023-0016

[39] Ofoedu, A. T., Ozor, J. E., Sofoluwe, O., & Jambol, D. D. (2024). A SCADA-integrated framework for real-time production monitoring and operational intelligence in FPSO units. *International Journal of Advanced Multidisciplinary Research and Studies*, *4*(6), 2453–2472. https://doi.org/10.62225/2583049x.2024.4.6.4450

[40] Gartoumi, K.I., Aboussaleh, M., & Zaki, S. (2024). Implementing lean construction to improve quality and megaproject construction: A case study. *Journal of Financial Management of Property and Construction*, *29*(1), 1–22. https://doi.org/10.1108/JFMPC-12-2022-0063

[41] Aderamo, A. T., Olisakwe, H. C., Adebayo, Y. A., & Esiri, A. E. (2024). AI-enabled predictive safeguards for offshore oil facilities: Enhancing safety and operational efficiency. *Comprehensive Research and Reviews in Engineering and Technology*, *2*(1), 23–43. https://doi.org/10.57219/crret.2024.2.1.0060

[42] Cheng, Z., Wan, H., Niu, H., Qu, X., Ding, X., Peng, H., & Zheng, Y. (2023). China offshore intelligent oilfield production monitoring system: Design and technical path forward for implementation. In *ADIPEC Conference*, (SPE-216490-MS). https://doi.org/10.2118/216490-ms

How to Cite: Palippui, H., Rosyid, D. M., Silvianita, S., & Sade, J. (2026). An IoT-Based Intelligent Monitoring System for Cargo Loss Detection in FPSO-Tanker Oil Transfer. *Journal of Computational and Cognitive Engineering*. https://doi.org/10.47852/bonviewJCCE62028129