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REAL-TIME IOT-BASED MONITORING AND ENVIRONMENTAL RISK ASSESSMENT OF NAEGLERIA FOWLERI IN SWIMMING POOL WATER

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Abstract

Naegleria fowleri, commonly known as the brain-eating amoeba, poses a serious and often fatal threat to human health in warm, poorly sanitized swimming pools. Direct pathogen detection is complicated, time-consuming, and expensive, making continuous environmental monitoring potentially valuable for identifying changing environmental conditions before they require operational intervention. A smart Internet of Things (IoT) based pool water quality monitoring system was developed using a physical sensor node equipped with four sensors: pH, temperature, water level, and chlorine. Data collected by an Arduino Uno microcontroller was transmitted via an ESP8266 Wi-Fi module to a centralized cloud platform. A threshold-based risk evaluation engine processed combined readings in real time to assess environmental risk conditions. The system was installed and tested under pool conditions for 10 to 15 days. The suggested model was used to classify the conditions in terms of risk based on the combination of temperature and free chlorine levels. While the system is configured to detect high-risk conditions when chlorine drops below 0.5 ppm, this threshold was not reached during the trial period. The results demonstrate the potential value of evaluating multiple parameters simultaneously for identifying environmental warning conditions. The proposed Aqua-Intel system is a scalable, cost-effective IoT solution that shifts the paradigm from reactive pathogen testing to proactive environmental risk assessment, supporting proactive swimming-pool water monitoring and risk assessment.

1. INTRODUCTION

Waterborne diseases have been a major public health issue especially in recreational water facilities like swimming pools. Of these, infections with the amoeba Naegleria fowleri, often referred to as the brain-eating amoeba, are uncommon but very deadly. The microorganism is a warm fresh water organism CDC describes N. fowleri as thriving in warm freshwater, and Stahl & Olson provides the scientific ecological basis and may invade the human body via the nasal passages causing primary amoebic meningoencephalitis (PAM) [1] a very

high mortality disease. Increasing temperatures and inadequate water management may influence the environmental persistence and distribution of N. fowleri, although the relative contribution of individual environmental factors remains incompletely understood [7]. Conventional ways of detecting the quality of water in swimming pools are based on manual testing that is usually time consuming, labor-intensive and cannot deliver real time information. With the arrival of Internet of Things (IoT), there is a new range of opportunities that have been created for environmental monitoring. These IoT-based systems are highly convenient in crucial applications such as water quality monitoring and preventing diseases because of the availability of continuous monitoring through sensors, real-time data analysis and alerts. [2]-[4].

Although the possible dangers associated with Naegleria fowleri are very well documented, the fact remains that the vast majority of swimming pools lack the means to monitor and control the contamination in the form of continuous monitoring systems. Currently existing methods of assessing the quality of water only serve as reactive measures and not pro-active as they can only detect problems once they pose a threat to health. Karachi makes a good example of a relevant region, where monitoring is required since Naegleria fowleri has already been identified in the water of that area [19]. In the situation, when real-time monitoring systems are absent, it greatly limits the options for the pool management and authorities. Thus, it is urgently necessary to have a smart, real-time surveillance system, which can identify environmental conditions associated with N. fowleri risk and issue early warnings. This study presents a smart Internet of Things (IoT) based pool water quality monitoring system designed to identify environmental risk factors associated with Naegleria fowleri proliferation. It is important to note that this system does not directly detect the pathogen itself, but rather monitors environmental and operational parameters associated with water quality and conditions relevant to N. fowleri risk. The goal of this study was to develop and evaluate a real-time IoT-based system for continuous monitoring of swimming-pool water and early identification of environmental conditions associated with N. fowleri risk. The targeted goals are:

The goal of this study was to develop & evaluate a real-time IoT-based system for continuous monitoring of swimming pool & early detection of environmental conditions associated with Naegleria Fowleri growth. Specifically, the study aims to monitor continuously water quality parameters temperature, pH, water level and chlorine levels, develop a real-time risk assessment model, and provide automated alerts for early intervention. The research will help in the development of technology as well as the safety of the population since it combines IoT and water quality measurements. The offered solution provides a proactive solution to identify dangerous conditions prior to turning into severe health risks. In terms of public health, timely identification of concerning environmental conditions may support earlier operational intervention. From a technological standpoint, it demonstrates the applicability of IoT in smart environmental monitoring and disease prevention. Moreover, the research is especially applicable in the case of the development of such urban centers as Karachi, where the state of the environment and the lack of infrastructure require the innovation and economical solutions. The suggested system can be modified to other water bodies and extended to other pathogens.

2. LITERATURE REVIEW

2.1 Existing Systems

Several recent systems demonstrate the application of Internet of Things (IoT) technologies for real-time water-quality monitoring, sensing, and automated data acquisition [1], [3], [5], [6]. We review four notable projects, summarizing their goals, main features, and limitations.

2.1.1 IoT-Based Smart Water Quality Monitoring System

Spandana et al. [1] implemented a wireless monitoring system utilizing temperature, pH, water level, and CO_2 sensors interfaced with an ARM microcontroller. In their design, data is transmitted via Wi-Fi to a web server to enable global access to real-time water metrics. Furthermore, the system is configured to trigger a local buzzer alert if sensors fail or out-of-range anomalies occur. Though useful for inexpensive deployment

and basic monitoring purposes, it does not have any predictive analysis capability and biological risk assessment.

2.1.2 SMS-Notified Swimming Pool Monitor

To enhance the user notification system, Purazo et al. [2] developed a microcontroller pool monitor that tests the pH level and temperature of the water, along with an SMS notification component. This device was created for educational purposes and sends a text message at a predetermined interval when the water needs to be drained from the pool for maintenance. It should be noted that the authors directly indicated the use of microbiological sensors in the future.

2.1.3 Low-Cost Multi-Parameter Water Quality Monitoring

An affordable multi-parameter system of water quality monitoring was created by Alam et al. [3]. It consists of several water-quality sensors installed on an embedded monitoring device that helps to monitor the necessary parameters and send the collected information for remote monitoring of water quality. This system proves the possibility of using low-cost sensors in combination with IoT for real-time water quality monitoring systems. This can decrease the necessity of regular manual measurements of water quality and allow identifying water changes promptly.

The system proposed by Alam et al. [3] can be considered relevant for the suggested system, as it proves the necessity of multi-parameter monitoring rather than using only one parameter for water quality control. Nevertheless, the presented system does not concern the swimming-pool environment and parameters associated with Naegleria fowleri. The proposed Aqua Intel system uses the suggested approach but also combines several parameters such as temperature, pH, free chlorine, and water level.

2.1.4 Smart Technologies and IoT-Based Water Resource Management

Palermo et al. [4] presented an overview of smart technologies for water resource management. Their review underlined the growing importance of IoT, sensing technologies, automation, data acquisition, and intelligent systems in modern water-management practices. The review discussed how interconnected sensors and communication technologies could facilitate real-time water monitoring and improve decision-making capabilities for water-related systems. The combination of sensing and digital technologies could enable more efficient monitoring and management practices than traditional systems based on regular manual measurements.

The findings of Palermo et al. [4] offer a more technology-oriented perspective on water monitoring than the current study. However, their paper does not focus on swimming-pool water quality or N. fowleri risk assessment practices. Hassan et al. [20] designed an IoT-based water-quality monitoring system for swimming pools. Their solution could be applied to the pool environment considered in the present study. The design by Hassan et al. [20] included real-time monitoring of water parameters, such as pH, chlorine, turbidity, and temperature. Thus, their solution is a closer match to the proposed system in terms of the object of monitoring. However, the systems described in Hassan et al. [20] are primarily aimed at general water-quality management, while the current study considered environmental risk factors associated with N. fowleri. The proposed Aqua Intel system is an extended version of similar IoT-based solutions found in the literature. It includes an additional feature of environmental risk classification intended to identify conditions associated with increased risks of N. fowleri presence.

2.2. Proposed System

The proposed Aqua Intel solution will be an IoT-based real-time swimming-pool water monitoring and environmental risk monitoring platform. The system currently on the market monitors water quality through periodic manual measurements, while the proposed system will gather water quality and operational data using a mixture of sensors and send measurements to a cloud platform for visualization and interpretation. IoT-based continuous multi-parameter monitoring for water quality has been proven feasible [1], [3], while

the possibilities of leveraging smart water-management concepts have been successfully illustrated through the adoption of connected sensing, automation and real-time data acquisition [4]. Specifically, Hassan et al. [20] have demonstrated an IoT-based swimming-pool water quality monitoring solution based on monitoring levels of pH, chlorine, turbidity, and water temperature. These show that IoT-based solutions are feasible for continuous monitoring of swimming-pool and other water environments.
However, current IoT-based swimming-pool monitoring systems largely monitor general water-quality indicators and sanitation status and are not designed explicitly as environmental risk classification systems oriented towards N. fowleri. The Aqua Intel system builds on the existing water-monitoring-based IoT systems by adding a novel layer: an environmental-risk classification layer oriented specifically to N. fowleri-related conditions. The system continuously monitors temperature, pH, free chlorine and water level, and feeds these observations through a proposed rule-based environmental risk model that classifies these conditions into risk categories using predefined environmental parameters, rather than providing a specific detection of N. fowleri.
Architecture The architecture of this system includes the sensing, wireless, cloud, and front end layers. The sensing layer comprised of an Arduino Uno and ESP8266-based sensors to measure and transmit temperature, pH, chlorine, and water-level measurements; these measurements are streamed to the cloud platform. The web and mobile front end displays real-time sensor measurements, historical data, risk status, and system status, and the mobile app makes it possible to monitor the system remotely. By streaming pool data to a platform, it is possible to monitor the swimming pool 24/7 and be alerted to any potential problems before they become critical.
Thus, the main contribution of our system is not the application of IoT swimming-pool monitoring technology (already demonstrated [20]), but the integrated multi-parameter environmental-monitoring and N. fowleri risk assessment layer that is, the environmental-risk screening based on integrated pool water quality parameters. Our environment-monitoring system offers an additional decision-support function, though our sensors cannot directly detect N. fowleri in swimming pools, but can only yield information that indirectly implies (by correlation of parameters) the existence or risk of existence of this microorganism. The confirmation of N. fowleri presence requires microbiological (biochemical, molecular) analysis in a specialized laboratory. Therefore, Aqua Intel is an ambient environmental screening system that can operate independently but in parallel with conventional pathogen detection laboratory services.

3. METHODOLOGY

Throughout this manuscript, chlorine concentrations are expressed in parts per million (ppm), which is mathematically equivalent to mg/L in dilute aqueous solutions. The threshold values are defined in ppm to maintain consistency with industry standards.

3.1 Research Design

This paper follows a design science and experimental research approach to design and evaluate a real-time IoT-based system for swimming-pool water monitoring and assessment of environmental conditions associated with Naegleria fowleri risk. The methodology centers on the development of an integrated approach consisting of sensor-based data collection, real-time processing and smart alert systems. To ascertain the use of the system in continuous monitoring and early risk detection. The prototype was deployed and evaluated under field conditions in a swimming-pool environment.

3.2 System Architecture

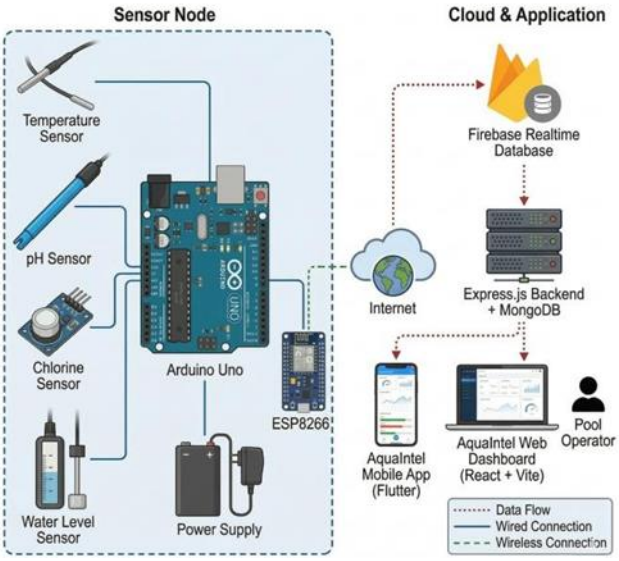


Figure 1. System Architecture of the Proposed IoT-Based Water Monitoring System

3.2.1 Sensing Layer

The sensing layer entails several sensors that are installed in the swimming pool to continuously measure certain parameters of water quality i.e. temperature, PH, chlorine and water level [1]-[3], [20]. The parameters are important indicators of the environmental conditions and general water safety of the pool.

3.2.2 Data Acquisition and Processing Layer

An Arduino Uno microcontroller is the key node of the sensor node that is used to collect raw data directly through the sensor using wired connections and perform initial preprocessing. The data is sifted and adjusted, and the complete physical node is maintained by a special power supply.

3.2.3 Communication Layer

The processed information is exchanged with the cloud through the ESP8266 module that creates a wireless Wi-Fi connection to the Internet [8]-[10]. This allows uninterrupted remote reporting as well as a real-time transfer of data between the physical pool and the cloud infrastructure enables wireless transmission of sensor data to the cloud platform for remote monitoring.

3.2.4 Application Layer

The cloud infrastructure handles the incoming data using Firebase Realtime Database to connect with the live data, an Express.js Backend, and MongoDB to store and process the data well. Lastly, the data is presented to the Pool Operator in two formats: the AquaIntel Web Dashboard (created with React + Vite) and the AquaIntel Mobile App (created with Flutter), which allow to monitor everything and issue immediate notifications.

3.3 System Workflow

3.3.1 Constant Data Monitoring

Aqua Intel system has several sensors in the swimming pool to constantly measure the main parameters of water quality, such as temperature, pH, Water level, and chlorine levels.

3.3.2 Edge Processing through Microcontroller

The sensor information is sent to a microcontroller (e.g. ESP8266/Arduino) and the sensor data is first processed, filtered, and aggregated to improve data consistency and support reliable monitoring.

3.3.3 Transmission of Data in the Real-Time

The processed data is then transmitted to a cloud-based system using wireless communication technologies like Wi-Fi or GSM that allows real-time data transfer.

3.3.4 Cloud-Based Analysis and Risk Assessment

In the cloud server, the system compares incoming data to predetermined safety limits and environmental conditions associated with Naegleria fowleri risk. An intelligent or a rule-based model is one that assesses the risk level (Safe, Moderate, High).

3.3.5 Automated Alert and Visualization System

Unsafe or high-risk conditions are identified and the system immediately sends alerts to the stakeholders through mobile apps, or dashboard indicators. At the same time, all information is presented on an easy-to-use dashboard to monitor and make decisions continuously.

3.3.6 Sensor Selection and Parameters

The success of the proposed system will be influenced by a proper measurement of significant environmental parameters relevant to Naegleria fowleri risk and pool-water quality.

Table 1. Sensors and their functions in the Smart Pool Monitoring System

Parameter	Sensor Type	Purpose
Temperature	Digital Temperature Sensor	Monitor warm-water conditions associated with N. fowleri environmental risk
pH Level	pH Sensor Probe	Measures acidity/alkalinity and supports assessment of pool-water quality and chlorine effectiveness.
Chlorine Level	Chlorine Sensor	Monitor free-chlorine levels relevant to pool-water disinfection.
Water Level	Ultrasonic Sensor	Measures Water depth in Pools

3.4 Risk Classification

Table 2. Risk Classification Logic

Temperature	Free Chlorine	Risk Level	Interpretation
≥30°C	**<0.5 ppm**	**High Risk**	High temperature combined with very low free chlorine represents the most concerning monitored condition.
≥30°C	**0.5–<1.0 ppm**	**Moderate Risk**	High temperature is accompanied by chlorine below the desired operational level, but not below the most critical threshold.
25–<30°C	**0.5–<1.0 ppm**	**Moderate Risk**	Elevated/warm temperature combined with reduced free chlorine indicates a condition requiring attention.
<25°C	**≥1.0 ppm**	**Safer**	Monitored temperature and free chlorine remain within the defined acceptable operational ranges.
25–<30°C	**≥1.0 ppm**	**Safer**	Temperature is below the high-temperature warning threshold and chlorine is at or above the operational minimum.
≥30°C	**≥1.0 ppm**	**Safer**	Temperature reaches the warning range, but adequate free chlorine is maintained.
<25°C	**0.5–<1.0 ppm**	**Moderate Risk**	Chlorine is below the defined acceptable operational level, even though temperature is lower.
<25°C	**<0.5 ppm**	**Moderate Risk**	Very low chlorine requires attention even when temperature is below the high-temperature warning range.

3.5 Environmental Risk Classification Model

A rule-based environmental risk classification model was developed to categorize monitored swimming-pool conditions into High Risk, Moderate Risk, and Safer categories. The model uses temperature and free-chlorine concentration as the primary parameters because these measurements are directly relevant to warm-water conditions and pool-water disinfection, respectively. The classification thresholds were defined as operational criteria for environmental risk screening and should not be interpreted as experimentally validated biological thresholds for Naegleria fowleri.

- **High Risk** is assigned when the water temperature is **≥30°C** and the free-chlorine concentration is **<0.5 ppm**. This combination represents the most concerning condition within the proposed model because a high-temperature warning condition occurs simultaneously with very low free-chlorine concentration.
- **Moderate Risk** is assigned when the free-chlorine concentration is **0.5–<1.0 ppm** under either the **25–<30°C** or **≥30°C** temperature ranges. Moderate Risk is also assigned when free chlorine falls below **0.5 ppm** while the temperature remains **<30°C**, since insufficient disinfectant residual requires operational attention even in the absence of the high-temperature condition.
- **Safer** conditions are assigned when free chlorine is **≥1.0 ppm** and the monitored parameters remain within the defined acceptable operational ranges. A temperature of **≥30°C** with free chlorine

maintained at **≥1.0 ppm** is therefore not classified as High Risk in the proposed model, although the elevated temperature remains a condition that should be monitored.

The **0.5 ppm chlorine boundary** was adopted as a conservative operational criterion informed by published chlorine-control and N. fowleri disinfection literature rather than as a biological growth threshold. Similarly, **30°C** was adopted as a proposed high-temperature warning threshold for environmental risk screening rather than as a universal N. fowleri growth threshold. The proposed classification therefore provides an operational early-warning mechanism and does not establish the presence or absence of N. fowleri.

4. RESULTS

4.1 Experimental Setup

The suggested IoT-based system was deployed with the help of several sensors, which were used to measure the parameters of swimming pool water in real-time. Data was sampled continuously over a 10–15-day observation period to monitor changes in temperature, pH, water level, and chlorine levels. Pool-water-quality guidance and published N. fowleri environmental and disinfection literature informed the selection of operational thresholds used in the proposed risk-classification model [7], [13]. It is important to note that during the 10–15-day testing period, the chlorine levels consistently remained between 0.8 and 1.2 ppm, meaning the system did not classify any observation as High Risk under the proposed risk-classification model. However, the system successfully identified multiple 'Moderate Risk' events and demonstrated its capability to detect risk conditions.

4.1.1 Temperature vs Time

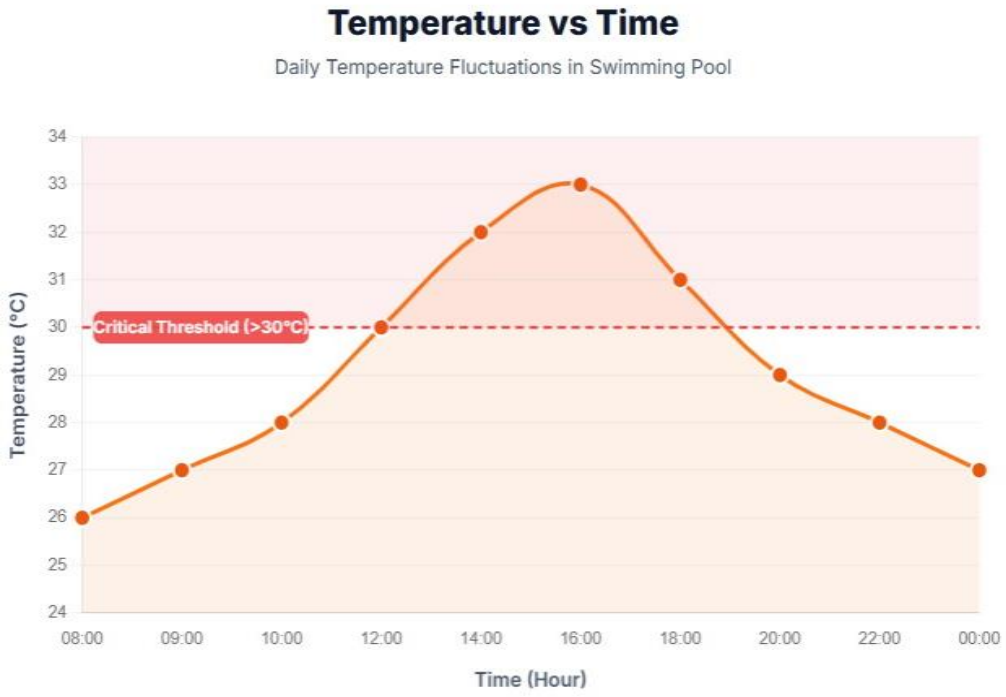


Figure 2. Temperature vs Time of Day. Highest temperature in the afternoon of 32 degrees Celsius to 33 degrees Celsius. N. fowleri is associated with warm-water environments [7]. Accordingly, temperatures at or above 30°C were treated as a high-temperature warning condition in the proposed operational model.

4.1.2 Chlorine Level vs Time



Figure 3. Chlorine level versus time of day. When the proposed classification logic is applied, free chlorine below 0.5 ppm results in a High-Risk alarm when the temperature is also met.

4.1.3 Multi-Parameter Monitoring (Combined Graph)

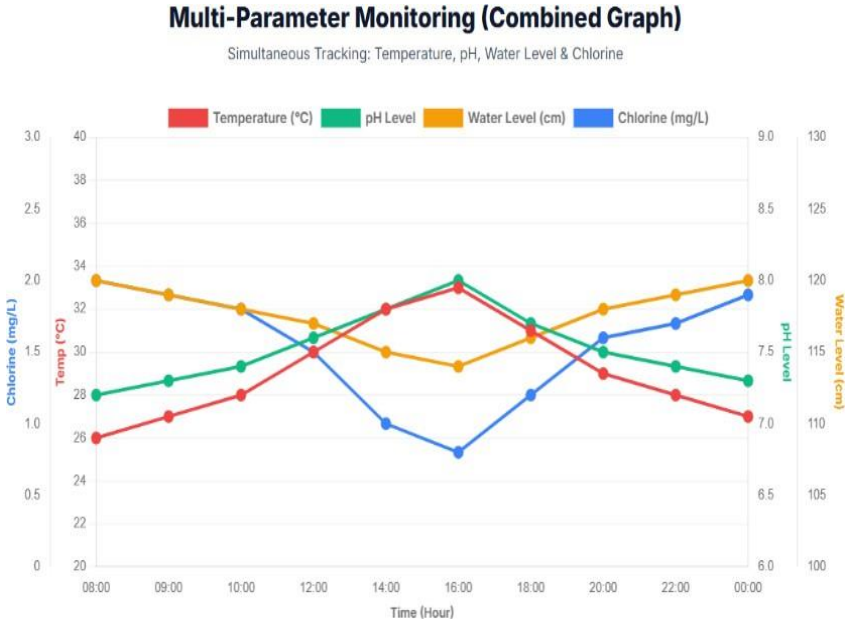


Figure 4. Graph of multi-parameter monitoring. Multi-parameter monitoring of temperature and free chlorine allowed the monitoring system to detect pre-determined warning conditions; water pH was monitored as an indicator of pool water quality and chlorine efficacy. During the experiment, there was no detected High-Risk condition due to free chlorine remaining above 0.5 ppm.

5. DISCUSSION

The results of this experiment show not only that the monitoring system proposed here is technically feasible but also offer insight into other aspects of monitoring free chlorines in pools. Afternoon peaks of temperature coincided with dips in free-chlorine concentrations. These time series results are consistent with the operational management complexities associated with the maintenance of water quality in changing pool-use

and environmental conditions; however, the causal effect of swimmer load, sunlight or other external factors were not directly observed in this experiment so the time series relationship, should not be taken to imply causality.

It was apparent from these monitoring results that the system was also capable of detecting transient changes in environmental conditions. Risk conditions in the classification model are apparent during times when temperature and free-chlorine measurements would be in the warning ranges of the system (Fig. 6). Multiple incidents, were a condition was detected for a period of time after the peak of temperature would have been recorded, have been illustrated by the graph, in which an operator would have had the opportunity to recognize the warning condition and respond with operational action. The effectiveness of any of these responses, however, was not explored in this paper. Continuous monitoring is of course meant to augment rather than replace conventional methods of pool-water management [20], [22], providing greater resolution and the detection of transient events.

Two moderate-risk events of less than 90 min duration are also shown in the figure and this again demonstrates the merits of monitoring continuously. For example, if testing was carried out on a regular basis then these short duration excursions may not have been detected in between the samplings. The proposed system collects sensor measurement data at all times allowing identification of these transient variations in real-time.The proposed risk classification model combines multiple parameters rather than relying on a single measurement. Temperature and free-chlorine concentration were given particular importance because warm-water conditions are associated with the environmental persistence and distribution of Naegleria fowleri, while adequate disinfectant residuals are important for controlling waterborne microorganisms [7], [13], [14]. However, the specific thresholds used in this study should be interpreted as operational criteria rather than experimentally established biological thresholds. In particular, the 0.5 ppm free-chlorine boundary was adopted as a conservative operational threshold informed by published chlorine-control guidance and N. fowleri disinfection studies. Evidence from drinking-water systems has shown that maintaining an adequate chlorine residual can contribute to the elimination or control of N. fowleri [14], while experimental studies have examined chlorine inactivation under controlled conditions [13]. Nevertheless, drinking-water guidance and laboratory disinfection studies cannot be directly interpreted as establishing a 0.5 ppm pathogen-specific threshold for swimming pools.

pH was included in the monitoring system because it is an important pool-water quality parameter and influences the effectiveness of chlorine-based disinfection. Current pool-water guidance recommends maintaining pH within an appropriate operational range, and elevated pH can reduce the effectiveness of chlorine as a disinfectant [22]. However, pH should not be interpreted as an independent N. fowleri biological-risk threshold in the proposed model. Previous research indicates that the relationship between pH and N. fowleri occurrence or persistence is more complex than a simple pH cutoff [7], [12]. Accordingly, the pH values monitored in this study are better understood as part of the overall water-quality and disinfection context rather than as direct indicators of amoebic growth.

The observed relationship between pH, temperature, and free chlorine also requires careful interpretation. Although periods of elevated pH coincided with changes in chlorine concentration in the experimental observations, the study was not designed to determine the chemical mechanism or causal rate of chlorine decay. Therefore, these observations are treated as dataset-specific patterns rather than evidence of a general chlorine-decay relationship. Future controlled experiments should investigate the interaction between pH, temperature, disinfectant concentration, and other pool-operational variables.

The indirect nature of the proposed N. fowleri risk assessment is an important consideration. The system does not directly detect or identify N. fowleri; instead, it evaluates environmental conditions that may be associated with increased environmental risk. N. fowleri occurrence and persistence are influenced by multiple abiotic and biotic factors, and environmental measurements alone cannot confirm the presence of the organism [7], [12]. Alternatively, from an environmental detection standpoint, the organism presence can be sampled by special microbiological or molecular methods (e.g.,qPCR-based detection [15]), which,

although offer significantly more direct evidence of organism presence, are not incorporated into the low-cost continuous sensor architecture described here.

The environmental risk model should therefore be considered a screening and decision-support tool, rather than a diagnostic for pathogen detection. A classification of 'high risk' indicates that the measured environmental parameters are within a set of warning ranges, but does not confirm that N. fowleri is in the water. A classification of 'safer' does not confirm that the pathogen is not present. This distinction is because the model thresholds were based on published disinfection and environmental evidence, but have not been validated against concurrent measurements of N. fowleri concentration in swimming-pool water [7], [13]–[15].

There are also some limitations of the system: First, the data were collected over only a 10-15 day period from one pool site. Longer data collection over much higher temperatures would reveal different patterns of temperature and levels of disinfectant. Second, other factors influencing pool chemistry-such as swimmer density, levels of sunlight, acidity (cyanuric acid), water circulation rates, etc.-were not directly measured and therefore their effects on the Aqua Intel measurements cannot be distinguished from those of the parameters studied by Aqua Intel. Third, the risk parameters proposed are not yet validated against direct microbiological or molecular assays for N. fowleri.

Longer term, multi-site testing in various other types of pools and throughout the seasons should determine the feasibility of this approach. Simultaneous collection of water samples for direct detection of N. fowleri (e.g., Q-PCR) [15] would provide direct evidence of pathogen occurrence, which could be used to compare against environmental sensors measurements [22]. This dataset could then be used to validate and refine the proposed thresholds, or test whether the combinations of pH, free chlorine residuals and temperature provide useful information on risk. Similarly, experiments could be performed to determine whether duration-based criteria might be used to discriminate between a brief sensor event and a more persistent environmental excursion. Machine-learning approaches represent another potential extension once sufficiently large and validated datasets become available. Previous research has demonstrated the application of machine learning to water-quality evaluation and IoT-based monitoring [11], [16], [17], while AI-enabled sensing approaches have also been explored for real-time water-quality applications [18]. However, machine-learning models should only be introduced after collecting adequate field data with reliable ground-truth measurements. A model trained only on sensor thresholds or the current short-duration dataset could reproduce the assumptions of the proposed rule-based model without providing independent biological validation.

Direct biosensing and molecular detection also represent promising future directions. Biosensor technologies have been investigated for rapid detection of waterborne pathogens [18], while broader biosensor research has demonstrated their potential for water-quality assessment and monitoring [21]. Integrating such technologies with the existing IoT architecture could eventually allow environmental screening and direct biological detection to operate within a common monitoring framework. Until such validation and integration are achieved, Aqua Intel should be considered an environmental monitoring and early-warning platform rather than a direct N. fowleri detection system.

Overall, the strength of the proposed approach lies in its combination of low-cost sensing, continuous data acquisition, cloud-based monitoring, and environmental risk classification. Existing IoT-based swimming-pool monitoring systems have demonstrated the feasibility of continuously monitoring conventional water-quality parameters [20]. Aqua Intel extends this concept by incorporating an environmental-risk classification layer oriented toward conditions associated with N. fowleri. The system therefore has potential value as a supplementary monitoring and decision-support tool, particularly in settings where continuous laboratory-based pathogen testing is impractical. Nevertheless, validation against direct N. fowleri detection and longer-term field observations is required before the proposed environmental thresholds can be considered reliable indicators of biological risk.

6. CONCLUSION

In the present study, we showed Aqua Intel, a low-cost real-time IoT-based application system for the detection of swimming-pool water parameters and environmental circumstances related to the Naegleria fowleri that results in NM. The system used various types of pH, temperature, free-chlorine and water-level sensors, an Arduino Uno with ESP8266-Internet-of-Things, and the Raspberry Pi to prepare and send measurements for real-time monitoring. The data are accumulated in a cloud-based web and mobile interface for easy viewing of the swimming pool environment and real-time tracking of parameter variations. The experimental deployment demonstrated the feasibility of continuous multi-parameter monitoring in a swimming-pool environment. During the observation period, the proposed risk classification model identified Moderate Risk conditions when the temperature reached the defined high-temperature warning range and free-chlorine concentration entered the corresponding warning range. The High-Risk condition, defined in the proposed model by a combination of high temperature and free chlorine below 0.5 ppm, was not observed during the trial period. The ability to identify short-duration changes in monitored conditions highlights the potential value of continuous monitoring as a supplement to conventional manual pool-water testing and management practices.

An important aspect of the proposed system is that it does not directly detect N. fowleri. Instead, it uses environmental and water-quality measurements to identify conditions that may be associated with increased environmental risk. Therefore, the risk classifications should be interpreted as an early-warning and decision-support mechanism rather than confirmation of pathogen presence or absence. The operational thresholds used in the proposed environmental risk model were informed by published literature and water-quality guidance; however, they should not be interpreted as experimentally validated N. fowleri biological thresholds. In particular, the 0.5 ppm chlorine boundary was adopted as a conservative operational criterion and requires further validation under actual swimming-pool conditions using direct microbiological or molecular detection methods. The study also has limitations, including the relatively short experimental period and deployment at a single pool site. Environmental conditions, pool-management practices, and seasonal variations may produce different monitoring patterns in other locations. In addition, factors such as swimmer density and sunlight intensity were not directly measured, and therefore their potential effects on temperature and chlorine levels could not be established from the present dataset.

Future work should focus on longer-term deployments across multiple swimming pools and different seasons, together with parallel laboratory-based detection of N. fowleri. Such data would also offer the ground truth needed to refine and validate the proposed risk thresholds. Larger data sets could facilitate developing machine-learning models for risk prediction. Coupling with molecular detection or biosensing would extend the system from continuous environmental monitoring to direct pathogen detection. In all, Aqua Intel points to the promise of linking low-cost IoT sensing, cloud monitoring, and environmental risk classification for on-going swimming-pool monitoring. This system does not seek to replace laboratory analysis or current pool management practices; instead, it aims to add another tier of monitoring and early detection to complement any existing procedures. With further validation and more extended periods of field testing, the approach could offer an accessible, scalable way to supplement swimming-pool water management, especially in low-resource settings.

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