



Bridging expert judgement and simulated evidence: A cross-validated IoT technology stack for African catfish (*Clarias gariepinus*) fingerling survivability

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ABSTRACT

Selecting an appropriate Internet of Things (IoT) technology stack comprising sensors, actuators, connectivity technologies, edge-computing devices, and cloud platforms is a critical step in developing aquaculture monitoring systems, yet technology selection is often unsystematic. This challenge is particularly important in resource-constrained environments, where cost, power availability, and connectivity reliability constrain system deployment and operation. This study aimed to identify, evaluate, and validate an appropriate IoT technology stack for monitoring African catfish (*Clarias gariepinus* Burchell, 1822) fingerling survivability. A mixed-methods sequential explanatory research design was adopted, integrating quantitative expert-survey data with simulation-based evidence. First, a structured questionnaire was administered to 48 IoT experts, of whom 87.5% reported direct implementation experience. The questionnaire demonstrated good internal consistency (Cronbach's $\alpha = 0.82$). Survey data were analyzed using descriptive statistics, including frequencies, percentages, and weighted rankings, to identify preferred sensors, actuators, connectivity technologies, edge devices, cloud platforms, and implementation priorities. Second, six simulation and prototyping platforms were comparatively evaluated against the requirements of aquaculture IoT development. Third, an independent 300-observation quasi-experimental simulation was conducted to examine the effects of key water-quality parameters on fingerling survivability. Multiple linear regression was used to estimate standardized sensitivity indices, which were subsequently compared with expert rankings for cross-validation. Dissolved oxygen sensors (16.79%), ammonia/nitrite sensors (14.18%), and temperature and pH sensors (11.57% each) received the highest expert rankings. For actuation, aerators and pumps (34.91%) and automated water-exchange systems (29.25%) received the highest rankings. Raspberry Pi Pico microcontrollers were identified as suitable edge-computing devices, with Message Queuing Telemetry Transport (MQTT) recommended for device communication, Wi-Fi for relatively close-range deployments, and Global System for Mobile Communications/Long-Term Evolution (GSM/LTE) for remote sites. ThingSpeak and Blynk were identified as suitable cloud platforms for data management and visualization. The principal implementation challenges were security (21.88%), interoperability (20.83%), and power consumption (19.79%). The simulation produced sensitivity indices of 0.7875 for dissolved oxygen, 0.7620 for ammonia, and 0.5462 for temperature, corresponding to the parameters receiving the strongest expert endorsement. The convergence between expert rankings and simulation-derived sensitivity indices provides evidence of consistency between practitioner judgment and simulated system behavior. The study therefore proposes a low-cost IoT technology stack comprising dissolved-oxygen and ammonia sensors, aeration and water-exchange actuators, Raspberry Pi Pico edge devices, MQTT-based communication, and ThingSpeak/Blynk cloud platforms for resource-constrained aquaculture environments. Adoption of standardized communication protocols, secure data transmission using Transport Layer Security (TLS), and low-power hardware designs is recommended to address interoperability, security, and energy constraints. The methodological framework also provides a basis for combining expert assessment with simulation-based evidence when evaluating IoT technologies for precision aquaculture and related agricultural applications.

Keywords: Aquaculture Sensors; African Catfish; Cloud Platforms; Edge Computing; Expert Survey; Internet of Things; Precision Aquaculture; Technology Assessment

I. INTRODUCTION

The application of Internet of Things (IoT) technologies to aquaculture has been widely proposed as a route to reducing fingerling mortality in African catfish (*Clarias gariepinus* BURCHELL 1822) production, where uncontrolled rearing conditions can produce mortality rates exceeding 50% (Gonzalez, 2018). However, the aquaculture IoT literature more often demonstrates that a given sensor, platform, or communication protocol can work in principle than it systematically determines which technologies are most applicable, cost-effective, and reliable for a specific production context (Rastegari et al., 2023). This is a consequential gap: sensor and actuator choices, connectivity technology, and cloud platform selection jointly determine both the capital cost of a system and its long-term operability in rural, power- and connectivity-constrained environments, yet these choices are rarely validated



through a combination of practitioner consensus and independent empirical evidence before being embedded in a proposed architecture.

African catfish is preferred by small-scale aquaculture across East and West Africa because of its fast growth, good feed-conversion ratio, tolerance of sub-optimal water-quality conditions, and suitability for high-density rearing (Jais et al., 2024). These production advantages are realised only if the fingerling stage, during which the majority of losses occur is actively managed. The initial 30–45 days after hatching are consistently identified as the period of greatest mortality risk, after which survival rates approach 100% (Ngugi et al., 2007). Manual monitoring regimes typical of small-scale hatcheries commonly leave water quality unchecked for 10–12 hours overnight, a gap that coincides with the period of greatest dissolved-oxygen depletion from algal and bacterial respiration in the absence of photosynthesis (Boyd, 2015); this operational blind spot, rather than any single environmental parameter in isolation, is what motivates continuous sensor-based monitoring as an alternative to periodic manual sampling. The specific goal of this paper is to identify the IoT technologies that are most appropriate for bridging this monitoring gap in a way that is both affordable and manageable for hatchery operators with limited resources.

This paper reports the technology-determination phase of a broader mixed-methods doctoral study, corresponding to the objective of determining IoT technologies applicable for managing African catfish fingerling ecosystems for survivability. Rather than proposing a technology stack on the basis of literature review alone, this study combines three complementary evidence sources: (i) a structured survey of 48 IoT experts, assessing which sensors, actuators, connectivity technologies and cloud platforms, practitioners consider applicable and which implementation challenges they consider most significant; (ii) a comparative evaluation of six variables and prototyping tools against the specific requirements of aquaculture IoT development and (iii) cross-validation of expert consensus against global sensitivity indices computed from an independent 300-observation quasi-experimental simulation, testing whether practitioner-endorsed sensor priorities are corroborated by the parameters that empirically exert the greatest influence on fingerling survivability. Beyond its particular application to catfish fingerling management, this triangulated approach (professional judgment verified against simulated system behavior) is meant to serve as a model for technology selection in precision-agriculture IoT research more broadly.

1.1 Statement of the Problem

African catfish (*Clarias gariepinus*) fingerling survival is strongly influenced by water-quality conditions, particularly dissolved oxygen, ammonia, temperature, and pH. The early fingerling stage is especially vulnerable to environmental fluctuations, making effective monitoring and timely management of water quality essential for maintaining survival and production performance (Ngugi et al., 2007; Boyd, 2015). However, small-scale aquaculture systems in resource-constrained environments commonly depend on periodic manual monitoring, which may leave important water-quality changes undetected between sampling intervals and delay corrective intervention (Boyd, 2015).

Internet of Things (IoT) technologies offer opportunities for continuous water-quality monitoring, automated control, and remote access to aquaculture data. Nevertheless, existing aquaculture IoT research has largely focused on demonstrating the functionality of individual sensors, communication technologies, or monitoring platforms rather than systematically determining which combinations are most appropriate for specific production contexts and resource constraints (Rastegari et al., 2023). Technology selection is particularly challenging in small-scale and rural aquaculture because system design must simultaneously account for cost, power availability, connectivity, interoperability, security, and technical capacity.

A further limitation is that technology-selection decisions are frequently based on technical specifications, literature evidence, or expert judgment without independent quantitative validation of whether the selected monitoring variables correspond to the factors that most strongly influence fish survivability. Consequently, there is a need for a systematic approach that combines practitioner expertise with simulation-based quantitative evidence to identify and validate an affordable, reliable, and context-appropriate IoT technology stack for monitoring African catfish fingerling survivability. Addressing this gap would provide an evidence-based basis for selecting sensors, actuators, connectivity technologies, edge-computing devices, and cloud platforms suitable for resource-constrained aquaculture environments.

1.2 Research Objective

To identify, evaluate, and validate an appropriate IoT technology stack, including hardware components, connectivity solutions, cloud platforms, and development tools, for cost-effective monitoring of African catfish fingerling survivability in resource-constrained aquaculture environments.



II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 IoT Architecture and Enabling Technologies

An IoT system is conventionally decomposed into four interacting layers: device hardware (the physical sensors, actuators, and embedded boards that bridge the physical and digital domains), device software (which aggregates readings and manages connectivity), a communication layer (the protocols and connectivity that carry data to the wider network), and a platform layer (where data is collected, processed, and presented) (Patel & Patel, 2016; Lee & Lee, 2015). At the sensing layer, temperature, dissolved oxygen, pH, turbidity, and ammonia sensors form the core aquaculture instrumentation set (Pathmudi et al., 2023), consistent with systematic evidence that temperature, dissolved oxygen, and pH are the most frequently prioritized water-quality parameters across published IoT aquaculture deployments (Prapti et al., 2022). Connectivity options are typically grouped by range and power profile: short-range Bluetooth Low Energy and radio-frequency identification (RFID) suit wearable or highly localized sensing; medium-range Wi-Fi (IEEE 802.11), Zigbee, and Thread cover single-site aquaculture facilities; and long-range, low-power wide-area network (LPWAN) technologies: LoRaWAN, NB-IoT, LTE-Cat M1, and Sigfox; extend coverage to remote or multi-pond sites at the cost of data rate, and are the technologies of choice where consistent Wi-Fi coverage cannot be assumed (Mekki et al., 2019). Table 1 summarizes the range, power and typical aquaculture use case across these categories, which framed the connectivity recommendations synthesized from the expert survey in Section 4.3.

Table 1

IoT Connectivity Technologies by Effective Range and Power Profile

Category	Technology	Typical Range	Power Profile	Primary Aquaculture Use Case
Short-range	Bluetooth Low Energy (BLE)	< 100 m	Very low	Wearable/localized sensor links, device commissioning
Short-range	RFID	< 10 m	Passive / very low	Fingerling batch and inventory tracking
Medium-range	Wi-Fi (IEEE 802.11)	50–100 m	Moderate–high	Single-site pond/tank monitoring, ESP32 gateways
Medium-range	Zigbee	10–100 m (mesh)	Low	Multi-sensor mesh within one facility
Medium-range	Thread	10–30 m (mesh)	Low	Smart-facility device interoperability
Long-range (LPWAN)	LoRaWAN	2–15 km	Very low	Multi-pond or remote-farm telemetry
Long-range (LPWAN)	NB-IoT	1–10 km (cellular)	Low	Remote monitoring via cellular infrastructure
Long-range (LPWAN)	LTE-Cat M1	Cellular coverage	Low–moderate	Medium data-rate remote telemetry
Long-range (LPWAN)	Sigfox	10–40 km	Very low	Ultra-low-bandwidth alerting

At the application layer, cloud platforms such as ThingSpeak and Blynk provide scalable storage, visualization and remote actuator control, with ThingSpeak's native MATLAB integration additionally supporting predictive modelling (MathWorks, 2020; Blynk IoT Platform, 2021). At the actuation layer, pumps, aerators, heaters, and automated feeders convert analytical outputs into physical correction, commonly triggered by simple threshold rules (Al-Fuqaha et al., 2015), such as aerator activation below a dissolved-oxygen setpoint (Boyd, 2015). The lightweight MQTT protocol is widely adopted for sensor-to-cloud transport (Al-Fuqaha et al., 2015), with ESP32-class microcontrollers serving as the typical edge gateway (Shete et al., 2024; Serepas et al., 2025).

2.1.2 IoT Applications in Aquaculture and Fish Farming

Deployed systems illustrate how this architecture has been instantiated for fish farming specifically. Idachaba et al. (2017) describe an integrated pond-controller architecture combining a microcontroller with temperature, pH, water-level, and light-based cleanliness sensors, electronically actuated water-exchange taps and a scheduled feed motor, with GSM connectivity providing remote status updates to the farm operator; the light-pulse cleanliness sensor detects turbidity-driven water-quality decline by measuring obstruction of a transmitted light beam, triggering an automated water change when a threshold is exceeded. This sensing–actuation–connectivity pairing matches the priorities independently identified by the expert respondents in this study, providing external corroboration that the technology stack recommended here is already in productive use rather than a purely theoretical construction from architectural principles. Comparable peer-reviewed deployments reinforce this pattern: an IoT-based fish-farm water-



quality monitoring system combining pH, temperature, and dissolved-oxygen sensing with cloud-based alerting has been field-validated in aquaculture ponds (Chen et al., 2022), and a low-cost water-quality sensor network with web-based visualization has been documented under comparable resource constraints (Gowda & Kader, 2023).

2.1.3 Regional and Local Evidence on IoT-Based Aquaculture Adoption

A growing international literature documents IoT-based water-quality monitoring for aquaculture, with systematic reviews reporting that most deployed systems pair sensor networks for pH, temperature, dissolved oxygen, and ammonia with cloud-based dashboards, measurably improving fish welfare through continuous, data-driven management (Flores-Iwasaki et al., 2025; Biazzi & Marques, 2023). Cost, connectivity, and maintenance nonetheless remain persistently reported constraints on scaling these systems in low-income production contexts, reinforcing the affordability and simplicity criteria used to select the technology stack recommended in Section 4 (Rodríguez et al., 2025).

Regionally, low-cost implementations using Arduino- and ESP32-class microcontrollers with Wi-Fi or GSM connectivity dominate developing-country deployments: a low-cost Arduino-based water-quality monitoring device with an automated alert system was developed and field-tested on domestic fish ponds in Nigeria, targeting pH as a key driver of fish losses (Babalola et al., 2024), while a NodeMCU-based system monitoring temperature, pH, and dissolved oxygen in catfish ponds specifically demonstrated that continuous IoT monitoring improves fish health and reduces disease risk relative to conventional periodic checks (Wibisono & Jayadi, 2024). Within Kenya specifically, an IoT-based framework incorporating artificial intelligence for small-scale aquaculture management (Omambia et al., 2025) illustrates an emerging but still nascent local evidence base, consistent with broader observations that aquaculture technology adoption in Kenya remains constrained by cost, awareness, and limited technical support rather than by farmer attitudes toward the technology itself (Cheruiyot & Adhiaya, 2023). Taken together, this evidence confirms that low-cost, commodity-hardware IoT monitoring is both technically viable and increasingly common in resource-constrained aquaculture settings, and that the sensor and connectivity choices converged upon by the expert respondents in this study track closely with what has already been field-tested elsewhere.

2.2 The Research Gap

What remains largely absent from this literature is a systematic, comparative determination of which specific technologies within each layer are most applicable to a given production context, validated by both practitioner consensus and independent quantitative evidence. Existing aquaculture IoT reviews (Rastegari et al., 2023; Sharma & Shivandu, 2024) catalogue the available technology space but do not report a structured expert assessment cross-validated against empirical sensitivity data, which is the specific gap this study addresses.

III. METHODOLOGY

3.1 Expert Survey Design and Sample

A structured questionnaire administered via Google Forms over a six-week fieldwork period, was completed by 48 IoT experts drawn from two institutions in Kenya: the Moi University Information and Communication Technology (ICT) Directorate ($n = 8$) and the iLabAfrica research and innovation Centre ($n = 40$), selected through purposive sampling for their expertise in the design, implementation, and application of IoT systems in agricultural and environmental contexts. Participants were recruited through direct invitation to institutional research leads, supplemented by professional referral from initial respondents and, at Moi University, personal contact with ICT staff already engaged in IoT projects. Respondents comprised IoT Engineers (33.3%), Data Scientists/Analysts (16.7%), User Interface Specialists (12.5%), Embedded Systems Engineers (8.3%), IoT Security Specialists (8.3%), IoT Architects (8.3%), and IoT Project Managers (8.3%), with the remainder in systems administration and sensor/actuator specializations. The majority (58.3%) had fewer than six years of IoT experience and 37.5% had six to ten years, indicating a respondent pool with substantial but not predominantly senior-level practical exposure; 87.5% reported direct implementation experience with IoT projects, most commonly in agriculture (68.8% of respondents' projects), followed by healthcare (39.6%), industrial IoT (37.5%), and water management (35.4%). a sector distribution in which agriculture, the domain most relevant to this study, was the single largest application area represented among respondents.

The questionnaire was organized in four sections, which are aligned with the wider objectives of the study: identification of critical water quality parameters, assessment of the relevant IoT technologies and sensor configurations, assessment of the theoretical frameworks relevant for the design of an integrated aquaculture model, and validation of the design criteria for the proposed integrated model, the latter of which is the main source of the results reported in section 4. Internal consistency of the instrument was confirmed by Cronbach's alpha ($\alpha = 0.82$).



The tool was reviewed for its content validity by academic supervisors and pre-tested by a pilot group of five IoT practitioners whose feedback informed the revisions of the ambiguous entries before its full release.

3.2 Simulation and Prototyping Tool Selection

Six simulation and prototyping tools: Wokwi, ThingSpeak, MATLAB/Simulink, Proteus Design Suite, iFogSim, and NS-3, were comparatively assessed against the specific requirements of the study: edge-device emulation, cloud-based data logging and visualization and advanced statistical/survivability modelling (Table 2). No single tool satisfied all three requirements, motivating an integrated selection of Wokwi (edge-level sensor and actuator emulation), ThingSpeak (cloud logging, visualization, and MATLAB-based analytics), and MATLAB (advanced statistical and survivability modelling) as the combined simulation environment used for the quasi-experimental validation reported in this study.

Table 2

Comparative Assessment of Candidate Simulation and Prototyping Tools for Aquaculture IoT Development

Rank	Tool	Primary Role	Key Strength	Key Limitation
1	Wokwi	Edge device simulation	Fast, browser-based, supports ESP32/Pico, free	Limited biological realism, weak analytics
2	ThingSpeak	Cloud IoT visualization & logging	Easy HTTP integration, MATLAB cloud analytics	Limited dashboard customization
3	MATLAB/Simulink	Advanced analytics & modelling	Publication-quality output, strong ML support	Slower prototyping, license cost
4	Proteus Design Suite	Hardware/circuit simulation	Accurate microcontroller/circuit simulation	Limited cloud integration, paid
5	iFogSim	IoT architecture & fog computing	Edge-cloud latency and scalability modelling	No real sensor simulation, Java-based
6	NS-3	Wireless network simulation	Research-grade protocol/network modelling	Steep learning curve, no hardware simulation

3.3 Simulation Environment and Experimental Configuration

The integrated simulation environment chosen in Section 3.2 was then set up to test the sensor, actuator and connectivity options found in the expert survey under repeatable and controlled conditions. Six virtual sensors: temperature, pH, turbidity, dissolved oxygen, ammonia, and water level; as well as three actuator classes: an aerator, a water pump and a heater were wired to the Raspberry Pi Pico W microcontroller, which served as the edge control unit, to create a virtual fish-tank environment in Wokwi that was programmed in Python (Table 3). In order to replicate the sensing-connectivity-analytics pipeline suggested in Section 4.3, sensor readings were sampled every minute, sent to a specific ThingSpeak channel via HTTP and exported to MATLAB for statistical analysis.

Table 3

Independent and Dependent Variables Monitored in the Simulation-Based Computational Experiment

Type	Variable	Description
Independent	Water temperature	measured in °C
Independent	Water turbidity	measured in NTU
Independent	Dissolved oxygen	measured in mg/L
Independent	Water level	measured in cm
Independent	pH	unitless pH scale
Independent	Ammonia	measured in mg/L
Dependent	Fingerling survivability index	composite index derived from parameter deviations

The threshold logic built into the firmware of the microcontroller shall activate each actuator if its associated parameters deviate from the safe range established in reviewed literature and independently confirmed as technically appropriate by the expert survey (Table 4): the water exchange pump when turbidity or ammonia is activated, the heater when the temperature is not ideal, and the aerator when the dissolved oxygen value is below the safe threshold.

**Table 4**

Safe and Critical/Extreme Ranges of Water-Quality Parameters Used as Actuator-Trigger Thresholds in the Simulation

Parameter	Safe Range	Critical / Extreme
Temperature	26–30 °C	< 5 °C or > 34 °C
Dissolved Oxygen	> 5 mg/L	< 3 mg/L
pH	6.5–8.5	< 5 or > 9
Ammonia (NH ₃)	< 0.2 mg/L	> 0.5 mg/L
Turbidity	< 50 NTU	> 150 NTU
Water Level	80–100 cm	< 7 cm

The random variable function of the Wokwi system was used to generate realistic fluctuations of all six parameters over 300 consecutive one-minute recording cycles, replicating the feed, metabolic and waste variability typical of an active fish tank without the costs, time and biological risks of live experiments. Two conditions were operated in the otherwise identical construction settings: an uncontrolled baseline, where parameters were allowed to move without corrective action, and an IoT-controlled condition, where the closed loop control logic described above was applied in a continuous manner. This paired design isolated the effect of automatic sensing and activation on the modelled survival outcome and the resulting per-cycle parameter and survival data formed the basis of the sensitivity analysis described in section 4.6. As the simulation environment does not reproduce sensor corruption, hardware degradation, power interruptions or the full biological variability of a living pond, its results are best interpreted as evidence of the model's internal logic and statistical coherence rather than as a field-validated measurement of the performance of the technology in practice.

3.4 Cross-Validation Approach

To test whether expert-endorsed technology priorities were empirically justified rather than reflecting familiarity or convention alone, sensor endorsement rankings from the expert survey were compared against global sensitivity indices (SI) computed from the independent 300-observation quasi-experimental simulation of the proposed model, in which each of the six monitored environmental parameters was systematically varied and its relative influence on the survivability index quantified. Sensitivity indices were computed as the absolute standardized beta coefficients from a multiple regression of the simulated survivability index on the six monitored parameters, reflecting each parameter's relative weighting within the fitted model rather than a variance-based global sensitivity method such as Sobol or Morris indices; the resulting rankings are therefore best interpreted as evidence of the model's internal parameter weighting, cross-checked against independent practitioner judgement, rather than as a field-validated measure of real-world parameter importance. Convergence between the two independent evidence sources: practitioner judgement and simulated system behaviour was interpreted as methodological triangulation supporting the validity of the recommended technology stack

IV. FINDINGS & DISCUSSION

4.1 Sensor Technologies

Table 5 summarizes the scientific support of the sensor types for fingerling ecosystem monitoring, reported both as a percentage of the total sensor endorsement and as a percentage of respondents who selected each sensor type (multiple selections were allowed, so the percentage of respondents selected was greater than 100). Dissolved oxygen sensors (9.57%; 64.2) and feeding sensors (9.33; 52.1) were the most frequently endorsed sensors (16.79%) and the type of sensor selected by the largest proportion of respondents (93.8) followed by ammonia and nitrite sensors (14.18%; 79.2) and temperature and pH sensors (both endorsed at a lower frequency). The consistency of the ranking for both metrics shows that dissolved oxygen and ammonia measurements were given a higher priority by the expert sample than by the small minority of highly rated respondents.

**Table 5***Expert-Endorsed Sensor Technologies (n = 48 Respondents, Multiple Selections Permitted)*

Sensor Type	n	% of Endorsements	% of Respondents (N=48)
Dissolved Oxygen	45	16.79	93.8
Ammonia / Nitrite	38	14.18	79.2
Temperature	31	11.57	64.6
pH	31	11.57	64.6
Water Level	26	9.70	54.2
Feeding	25	9.33	52.1
Turbidity	21	7.84	43.8
Camera / Imaging	19	7.09	39.6
Water Flow	16	5.97	33.3
Light	11	4.10	22.9

4.2 Actuator and Actuation Technologies

Table 6 summarizes the scientific support for the sensor types for fingerling ecosystem monitoring, reported both as a percentage of the total sensor endorsement and as a percentage of respondents who selected each sensor type (multiple selections were allowed, so the percentage of respondents selected was greater than 100). Dissolved oxygen sensors (9.57%; 64.2) and feeding sensors (9.33; 52.1) were the most frequently endorsed sensors (16.79%) and the type of sensor selected by the largest proportion of respondents (93.8) followed by ammonia and nitrite sensors (14.18%; 79.2) and temperature and pH sensors (both endorsed at a lower frequency). The consistency of the ranking for both metrics shows that dissolved oxygen and ammonia measurements were given a higher priority by the expert sample than by the small minority of highly rated respondents.

Table 6*Expert-Endorsed Actuator Technologies (n = 48 Respondents, Multiple Selections Permitted)*

Actuator Category	n	% of Endorsements	% of Respondents (N=48)
Aerators / mechanical pumps	37	34.91	77.1
Water-exchange valves / pumps	31	29.25	64.6
Heaters / coolers	11	10.38	22.9
UV sterilisation lamps	6	5.66	12.5
Ultrasonic algae control	5	4.72	10.4
Chemical dosing pumps	4	3.77	8.3
Automated feeders	4	3.77	8.3

Table 6*Applied Actuation Systems at the System Level (n = 48 Respondents, Multiple Selections Permitted)*

Actuation System	n	% of Respondents (N=48)
Aeration systems	35	72.9
Temperature control systems	30	62.5
Water exchange systems	26	54.2
UV sterilization systems	12	25.0
Chemical dosing pumps	10	20.8
Algae control systems	10	20.8
Feeders with adjustable dispensing	6	12.5
Sediment settling systems	5	10.4

4.3 Connectivity, Edge, and Cloud Platform Recommendations

Experts and an accompanying literature review have focused on ESP32 and Arduino Uno (or similar boards of the Raspberry Pi family) as the appropriate edge components for data acquisition and local control logic, with the recommended lightweight MQTT protocol for cloud-to-cloud data transfer. Wi-Fi (IEEE 802.11) is recommended for small or close-field installations, while GSM and LTE are recommended for larger or far-field installations, where consistent Wi-Fi coverage cannot be guaranteed. The combination of ThingSpeak and Blynk cloud platforms has been confirmed: ThingSpeak for time series data storage, MATLAB visualization and statistical analysis, and Blynk for mobile dashboard access, threshold triggering and remote control of actuators, in line with the Internet of Things layered architecture. These recommendations are mapped directly to the connectivity, storage and interface layers of



the recommended stack: the ThingSpeak cloud data storage and predictive analytics layer provides a mobile alerting interface and a remote override interface to enable farm operators to receive alerts for cloud-based breaches, and a light MQTT message over Wi-Fi for multi-pond deployments.

4.4 Commonly Monitored Fingerling-Ecosystem Parameters

Regardless of the specific sensor hardware approved, respondents were asked which environmental parameters should be prioritized for continuous monitoring in the fingerling ecosystem. Table 8 shows that temperature, dissolved oxygen and ammonia were each identified by 83.3%, 81.2% and 72.9% respondents as the most important parameters for monitoring, respectively, although the percentage of respondents who supported sensor technology varied considerably, reflecting the fact that turbidity and pH sensors are less commonly used in practice than the underlying parameters.

Table 8

Commonly Monitored Parameters in the Fingerling Ecosystem (n = 48 Respondents, Multiple Selections Permitted)

Monitored Parameter	n	% of Respondents (N=48)
Temperature	40	83.3
Dissolved Oxygen	40	83.3
Ammonia	40	83.3
pH	39	81.2
Turbidity	35	72.9

4.5 Implementation Challenges and Mitigation Strategies

95.8% of respondents reported having experienced challenges during IoT implementation. Table 9 presents the overall distribution of implementation-challenge categories, both as a share of all challenge endorsements and as the percentage of the 48 respondents who identified each category; security concerns (87.5% of respondents), interoperability issues (83.3%), power consumption (79.2%), and reliability/maintenance difficulties (60.4%) were the most widely reported, with data-management/analytics (47.9%) and standardization/regulatory gaps (37.5%) reported less frequently.

Table 9

Overall IoT Implementation Challenge Categories

Challenge Category	n	% of Endorsements	% of Respondents (N=48)
Security concerns	42	21.88	87.5
Interoperability	40	20.83	83.3
Power consumption	38	19.79	79.2
Reliability and maintenance	29	15.10	60.4
Data management and analytics	23	11.98	47.9
Standardisation and regulation	18	9.38	37.5

Table 10 summarizes, for each of five recognized challenge categories, the single most frequently cited specific challenge and the corresponding most frequently recommended mitigation. For security, the leading challenge was the absence of standardized security protocols (79.2% of respondents), addressed primarily through adherence to recognized security standards and frameworks such as ISO/IEC 27001 (85.4%); for interoperability, protocol and standards diversity (87.5%) was addressed through adoption of standardized communication protocols (93.8%); for power management, limited battery life (91.7%) was addressed through low-power hardware and energy-efficient processor selection (91.7%), with lightweight protocols such as MQTT-SN (87.5% of respondents) and solar power backup (75.0%) also frequently recommended; for ongoing maintenance, device-management burden and power management were jointly the most cited challenges (72.9% each), addressed primarily through real-time remote telemetry and device-health monitoring (87.5%); and for sensor deployment specifically, biofouling and the resulting calibration burden (79.2%) and the high capital cost of industrial-grade sensors (68.8%) were the dominant concerns, addressed through selection of ruggedized, corrosion-resistant, aquaculture-appropriate sensors (91.7%) and wireless sensor networks that reduce complex wiring.

**Table 10**

Summary of Top Implementation Challenges and Corresponding Recommended Mitigation Strategies, by Category

Challenge Category	Top Challenge (% of Respondents)	Top Recommended Solution (% of Respondents)
Security	Lack of standardized security protocols (79.2%)	Adherence to established security standards/frameworks (85.4%)
Interoperability	Diversity of protocols and standards (87.5%)	Adoption of standardized communication protocols (93.8%)
Power management	Limited battery life (91.7%)	Low-power hardware components and energy-efficient processors (91.7%)
Maintenance	Device management/updates and power management (72.9% each)	Real-time remote telemetry and device-health monitoring (87.5%)
Sensor deployment	Sensor fouling and calibration burden (79.2%)	Ruggedized, corrosion-resistant, aquaculture-appropriate sensors (91.7%)

4.6 Convergent Validation: Expert Consensus versus Simulated Sensitivity

Table 11 compares expert sensor endorsement rankings against global sensitivity indices independently computed from the 300-observation quasi-experimental simulation. The two evidence sources converged closely in rank order: dissolved oxygen was ranked first by both experts and simulation, ammonia second, and temperature third, with the two lower-priority parameters (turbidity, water level) similarly ranked lowest by both methods. This convergence between independently collected practitioner judgement and independently computed simulated system behaviour provides methodological triangulation supporting the validity of the recommended sensor priorities.

Table 11

Cross-Validation of Expert Sensor-Endorsement Percentages against Simulation-Derived Global Sensitivity Indices

Parameter	Expert Endorsement (%)	Sensitivity Index (SI)
Dissolved Oxygen	16.79	0.7875
Ammonia	14.18	0.7620
Temperature	11.57	0.5462
pH	11.57	0.2137
Turbidity	7.84	0.1954
Water Level	9.70	0.1263

4.7 Discussion

The convergence between the expert consensus and the simulated sensitivity indices (Table 11) is the main methodological finding of the paper: it shows that the preferred technology for this application is not only a question of convention or sensor availability but also confirmed by parameters that independently have the largest quantitative impact on the survival of the fingerlings. This convergence strengthens the confidence in the resulting technology stack beyond what any single evidence source could support and provides a model for an expert survey cross-validated by a sensitivity analysis based on simulation, which could be used for the selection of technologies in other IoT contexts, where the cost of deployment makes trial and error impractical. This pattern is consistent with independent work combining IoT sensor data with machine learning to predict fish species survival directly from water-quality metrics, which likewise identifies temperature and dissolved oxygen as leading predictors of survival outcomes (Islam et al., 2023). The dominance of security, interoperability and energy consumption as barriers to implementation reinforces the findings of the wider literature on the Internet of Things (Boeckl et al., 2019; Al-Fuqaha et al., 2015; Ahmed et al., 2025). The high reported fouling and calibration burden of sensors (79.2%) and the expense of sensors make this especially pertinent in the context of aquaculture. This suggests that the choice of technology for small scale aquaculture farms should take into account maintenance and total ownership costs in addition to sensing performance, partly reflecting the fact that dissolved oxygen and ammonia have been independently confirmed as the dominant drivers of survival, justifying sensor investments even in the context of limited overall budgets.

Beyond the technical level itself, it is likely that adoption will be shaped by factors outside the scope of the technology determination exercise presented here. The farmers surveyed for the broader study cited costs, network connectivity and technical literacy as their main concerns about the adoption of the IoT, but expressed a near unanimous willingness to adopt automatic monitoring if these obstacles were addressed, suggesting that the barriers to adoption of the recommended technology stack are mainly economic and infrastructural rather than behavioral. This is in line with the emphasis in both the expert review and the broader literature (Rodriguez et al., 2025) on low-cost, commodity-grade open-source platforms as a requirement rather than a compromise and reinforces the practical



importance of preferring open source and ARD-based controllers and cloud platforms to proprietary industrial grade alternatives. Cost-efficiency is also reported to be the main driver of the adoption of the Internet of Things by SMEs in general, and by aquaculture in particular (Ghafari et al., 2024), which gives further weight to the affordability criterion used in the technology selection reported here.

The proposed technology stack is open-source and commodity-grade, which aligns with previous recommendations for low-cost aquaculture IoT design in developing-country contexts (Babalola et al., 2024; Wibisono & Jayadi, 2024). In contrast to other proposed single-source technology stacks from literature review alone, the stack reported here has been independently verified through practitioner consensus and sensitivity evidence derived from simulation.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

This paper systematically triangulated IoT technologies suitable for improving African catfish fingerling survivability. It combined a survey of 48 experts, a comparative evaluation of six simulation and prototyping tools, and cross-validation using independently calculated sensitivity indices. The findings identified dissolved oxygen and ammonia sensors, aeration and water-exchange systems, Raspberry Pi Pico, edge devices with MQTT connectivity, and ThingSpeak and Blynk cloud platforms as the most suitable technology stack. Key concerns such as interoperability, standardization and power consumption were also considered. The strong agreement between expert opinions and simulation-based sensitivity rankings strengthens the credibility of these recommendations. This convergence demonstrates a reliable and reproducible approach for selecting IoT technologies in precision agriculture and aquaculture. It also shows how expert surveys and simulations can be effectively combined for technology validation in resource-constrained environments. The recommended technology stack is based entirely on low-cost, open-source, and widely available components. As a result, it addresses the cost and maintenance challenges highlighted by both experts and farmers as major barriers to adoption. These findings are therefore practical and immediately applicable to hatchery operators and system integrators working in resource-limited aquaculture settings.

5.2 Recommendations

Based on these findings, the following are recommended: (i) hatchery operators and system integrators should prioritize dissolved-oxygen and ammonia sensing, as these parameters were independently confirmed by both expert consensus and simulation-derived sensitivity indices as the dominant drivers of fingerling survival; (ii) system designers should adopt open-source, commodity-grade components, specifically Raspberry Pi Pico edge devices with MQTT connectivity, and ThingSpeak or Blynk cloud platforms, to keep capital and maintenance costs within reach of small-scale operators; (iii) implementers should build in standardized communication protocols and TLS/SSL encryption at the design stage to pre-empt the interoperability and security concerns most frequently raised by experts; (iv) connectivity choice should be matched to site conditions, Wi-Fi for single-site facilities and GSM/LTE or LPWAN options for remote or multi-pond deployments; and (v) future work should pursue field validation of the proposed stack under live hatchery conditions, including sensor calibration drift and failure-rate testing, and should extend the expert sample beyond the two Kenyan institutions surveyed here to test the generalizability of these recommendations across other African aquaculture-producing regions.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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