Modelling African Catfish Fingerling Survivability with a Seven-Layer IoT Architecture: The Integrated Cyber-Ecological IoT Survivability Framework

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Article History
Received: 2026.03.09
Revised: 2026.08.18
Accepted: 2026.08.22
Published: 2026.08.28

Keywords
African catfish
Aquaculture
Internet of Things
Survivability

How to cite:
Shitote, S. K., Ondulo, J., & Odoyo, C. (2026). Modelling African Catfish Fingerling Survivability with a Seven-Layer IoT Architecture: The Integrated Cyber-Ecological IoT Survivability Framework. *Journal of Research and Academic Writing, 3*(2), 135-150.

Abstract
African catfish (*Clarias gariepinus* Burchell, 1822) is a valuable aquaculture species in Africa, but fingerling mortality driven by poor water-quality and cannibalism remains a key constraint on production. Drawing on a mixed-methods survey of twelve catfish farmers and forty-eight IoT practitioners in Kenya, this paper proposes a seven-layer Internet of Things (IoT) architecture for environmental and behavioural management of the fingerling ecosystem, integrating four complementary theories with real-time sensing and threshold-based automated actuation. The model was evaluated through a simulation-based computational experiment, comparing an automated control scenario against an uncontrolled baseline. Modelled mortality fell from 59.7% to 22.5% under the automated control scenario relative to the uncontrolled baseline. Because no live fish were reared or observed, these figures describe the model's behaviour under author-specified virtual conditions and should be read as an upper-bound estimate rather than a demonstrated biological outcome. Multiple linear regression identified dissolved oxygen and ammonia as the strongest predictors of the modelled survivability index (R^2 = 0.846, RMSE = 0.128). The seven-layer architecture is proposed as a scalable, low-cost design for resource-constrained aquaculture, with an estimated capital cost of approximately KES 52,000 (USD 400) for a reference single-pond configuration. The study introduces the Integrated Cyber-Ecological IoT Survivability Framework (ICEISF), synthesising General Systems, Water-Quality, Fish Behaviour and Physiology, and Cyber-Physical Systems theories; only the water-quality construct currently has simulation-based quantitative support. The model contributes a testable, cost-specified architecture to precision fish farming and digital aquaculture.

Introduction

The rapid spread of digital technologies, particularly the Internet of Things (IoT), embedded systems, wireless communication, cloud computing and data analytics, has fundamentally altered the monitoring and management of complex physical environments, especially when multiple interdependent factors interact dynamically, and a delay in response can lead to substantial losses (Ullah et al., 2025; Uddin, 2025). The fingerling ecosystem, as defined in this study, includes critical water-quality parameters (temperature, pH, dissolved oxygen, ammonia concentration, turbidity and water-level) and behavioural stressors (feeding competition and cannibalistic triggers), which interact dynamically. Deviations from optimal conditions can rapidly cause stress, disease, and mortality in intensive rearing environments for African catfish (*Clarias gariepinus* Burchell 1822) fingerlings (Boyd, 2015; Makori et al., 2017).

Although the adoption of Internet of Things (IoT) tools in aquaculture is increasing, most existing systems remain limited to passive data collection and visualisation rather than automated control (Idris et al., 2025). To address this gap, a design brief was established through a mixed-methods survey of twelve African catfish hatchery farmers in Western Kenya and forty-eight IoT practitioners. The survey revealed critical operational requirements across both groups. Farmers identified overnight dissolved oxygen depletion, disease, overfeeding, and water-quality deterioration as the primary drivers of mortality. Furthermore, respondents unanimously expressed willingness to adopt automated monitoring systems if cost, connectivity, and technical literacy barriers were addressed. Concurrently, IoT practitioners identified dissolved oxygen, ammonia, temperature, and pH as the most essential sensing parameters, while citing power scarcity, connectivity, and security as their main implementation challenges. Based on these field-derived priorities, a seven-layer IoT architectural model was designed to advance beyond passive monitoring toward integrated ecosystem management for African catfish fingerling production. This model integrates automated control mechanisms alongside real-time monitoring capabilities. The evaluation presented in this study is strictly limited to a simulated environment and does not constitute a live-fingerlings trial.

The design and development of the IoT model was guided by four complementary theories that together provide ecological, physicochemical, technological and behavioural foundations for the integrated architectural model.

According to General Systems Theory (Von Bertalanffy, 1968), the catfish rearing pond is an ecosystem that consists of interacting physical, chemical, and biological components in which changes in one parameter affect the entire system; therefore, environmental parameters (temperature, pH, dissolved oxygen, ammonia, turbidity, and water-level) must be monitored and regulated as interdependent variables rather than in isolation.

Water-Quality Theory (Boyd and Tucker 2012) regulates the water-quality for fish survival and growth, and water-quality is determined by temperature, pH, dissolved oxygen, ammonia and nitrite, with temperature directly affecting metabolism and growth, pH affecting biochemical activity and nutrient availability and dissolved oxygen essential for respiration. Un-ionised ammonia (NH_3) is toxic to gill and gut tissue, with toxicity concentrations varying with temperature, pH and total ammonia levels (Boyd and Tucker 2012). Therefore, a conservative design threshold of 0.02 mg/L un-ionised ammonia is used across the model (Sections 2.2 and 3.5), which is below the empirically determined effect-onset threshold of 1.25 mg/L NH_3 that corresponds to the 10% effect concentration (EC10) for reduced feed intake in Clarias gariepinus (Schram et al. 2010), ensuring that automated control actions occur before measurable physiological or growth impairments occur. These scientific thresholds and control rules enable the decision engine, which determines the automatic activation logic needed to sustain water-quality for fingerling production.

The technological aspect of this study is based on Cyber-Physical Systems theory, which explains how physical processes can be linked to computational and network elements by means of sensors, controllers, and cloud platforms (Lee, 2008). CPS theory explains why the threshold-triggered sensing-action architecture of the IoT model has been adopted and how it establishes the physical pond environment as a system that is constantly monitored and, in the design proposed here, controlled in a responsive way; this study reports the architecture's decision logic rather than a measured closed-loop control response (see Section 3.4). Recent work suggests that combined sensing, computation and control CPS architectures are an effective design pattern for IoT aquaculture systems, supporting both automated and human control within the same monitoring-and-actuation loop (Kularbphettong et al., 2026).

Fish Behaviour and Physiology Theory (Sloman, 2011) explains the effect of environmental conditions on feeding, stress, respiration, immunity, aggression and cannibalistic behaviour in fingerlings. The theory has been used conventionally to understand fish biology and only rarely to inform behavioural triggers for proactive IoT-based intervention. It provides the biological and behavioural basis for monitoring critical parameters and automating feeding schedules and environmental regulation to reduce stress, cannibalism and mortality of African catfish fingerlings. Cannibalism is particularly likely when feeding-frequency is low or stocking-density is high relative to available resources (Baras, 2013); for *Clarias gariepinus* specifically, the dominant driver of sibling cannibalism is size heterogeneity within the cohort, which is why size-grading is standard hatchery practice. Size dispersion and grading are not represented in the model's state vector or mitigation layer; the present model addresses cannibalism only through feeding-frequency and stocking-density management and does not implement size-based grading as a mitigation mechanism. The fingerlings addressed by this model are post-metamorphic fry with a mean weight of approximately 2–4 g and a total length of 3–5 cm. This is the stage at which hatchery operators typically transfer fish from nursery to grow-out systems and when cannibalism and water-quality sensitivity have the greatest impact on survival. Clarias gariepinus is a facultative air-breather, obtaining atmospheric oxygen through a paired suprabranchial (arborescent) organ in addition to its gills. This accessory air-breathing ability helps the species tolerate short periods of low dissolved oxygen better than obligate water-breathers. However, it does not remove the risk of mortality from prolonged hypoxia, ammonia toxicity, or other water-quality stressors addressed by this model. Therefore, it is not represented as a state variable in the model.

The integrated conceptual framework illustrates the relationships between ecosystem challenges, IoT technologies, and fingerling survivability. Within this framework, environmental, biological, and management factors serve as independent variables. IoT technologies act as mediating variables that monitor, analyse, and regulate these factors. Fingerling survivability represents the primary dependent variable, quantified using a survivability index and water-quality stability metrics. Data flows sequentially through a threshold-triggered sensing-and-actuation architecture grounded in four underlying theories. Sensors relay real-time environmental data to a microcontroller gateway, which routes the information to cloud platforms for intelligent analytics. When monitored metrics breach established baseline thresholds, the system automatically triggers corresponding actuators to restore ecosystem equilibrium. Operationally, this mechanism functions as a threshold-triggered, on/off reaction. This design is explicitly designated as threshold-triggered sensing-and-actuation architecture.

Research Design

This study adopted a pragmatic research paradigm using a sequential exploratory design, where qualitative field findings directly informed a quantitative, simulation-based computational experiment (Creswell & Creswell, 2018; Saunders et al., 2023). The initial exploratory phase, comprising semi-structured interviews with 12 catfish hatchery farmers and questionnaires completed by 48 Kenyan IoT practitioners, established the operational baseline for the model. This field data identified dissolved oxygen, temperature, ammonia, and pH as critical monitored parameters, while highlighting overnight monitoring gaps and lack of frequent feeding-linked cannibalism as primary drivers of mortality. These empirical insights directly justified the scenario parameters used in the second phase, which evaluated the decision logic of the proposed IoT model purely through computational simulation without rearing or observing live-fingerlings. Ethical approval for the farmer interviews and practitioner survey was obtained from Masinde Muliro University of Science and Technology Ethical Review Committee (MMUSTERC) and research permit through NACOSTI (number 837613), and all participants gave informed consent prior to participation. The practitioner survey was distributed to a sampling frame of 60 participants from three institutions in Kenya, yielding 48 completed responses rate of (80%).

Experimental Simulation

In the simulation phase, the Wokwi microcontroller simulator and ThingSpeak IoT analytics platform were used to exercise the decision logic and monitor the water-quality parameters relevant to the welfare of African catfish fingerlings. Wokwi simulates microcontroller and peripheral electronics behaviour; it does not model water chemistry, oxygen transfer, nitrification, or fish physiology, so the sensor values used in this study were authored by the researchers as scripted input ranges rather than produced by any physical or biological process. Wokwi provided a platform for designing and exercising the fish-tank control logic against virtual sensors (temperature, pH, turbidity, dissolved oxygen, ammonia, water-level) and virtual actuators (heater, aerator, feeder, water-pump). The ThingSpeak service was a cloud-based data management platform to which the simulated readings were logged, stored, visualised, and retrieved by API request for analysis in MATLAB. In total, 300 observations at 60-second intervals were logged from the continuously-varying scenario used for the regression and sensitivity analysis, representing five hours of simulated operation; a separate paired comparison of the two distinct automated and uncontrolled scenarios (300 controlled and 300 uncontrolled observations, 600 total, verified against the approved ThingSpeak exports) was used, and a between-scenario descriptive and t-test comparison reported.

The simulation evaluated system performance across an uncontrolled baseline and an automated IoT-controlled-scenario, with all values verified against approved simulation. The baseline scenario reflected uncontrolled conditions: temperature (13.76–27.13°C), dissolved oxygen (0.82–8.31 mg/L), pH (7.90–8.14), ammonia (0.0066–0.133 mg/L), turbidity (57.02–185.0 NTU), and water-level (49.20–87.33 cm). The controlled-scenario applied automated actuator responses triggered by threshold violations to enforce target design ranges (temperature: 26–30°C; DO: >5 mg/L; pH: 6.5–8.5; ammonia: <0.02 mg/L; turbidity: <50 NTU; water-level: 80–100 cm). The controlled operating ranges showed significant parameter management, despite brief deviations from design limits before feedback loops stabilised conditions: temperature (18.19–34.57°C), dissolved oxygen (1.50–10.50 mg/L), pH (6.85–8.25), ammonia (0.0050–0.0971 mg/L), turbidity (10.0–20.11 NTU), and water-level (91.43–106.0 cm).

Data Analysis

Descriptive statistics of the simulation data were computed and MATLAB was used for multiple linear regression, correlation and sensitivity analysis. Between-scenario differences in water-quality parameters and survivability were tested using Welch's independent-samples t-test (Section 3.1), and the two conditions' population survival distributions were additionally compared using Kaplan-Meier survival analysis with a log-rank test (Section 3.3).

Results and Discussion

Simulation Results: Extreme-Condition Stress-Test (Automated vs. Uncontrolled)

This subsection presents a deliberately extreme pair of edge-case scenarios, with severe parameter deviations well beyond what is typical for unmanaged ponds, to stress-test the decision-making engine's responsiveness within its operating range; it is not intended to represent typical unmanaged pond conditions, but rather to provide a continuous variable data base on which to base the regression and the main mortality. The following descriptive statistics were directly computed from the simulated data exported of n = 300 (controlled) and n = 300 (uncontrolled) simulation and are summarised in Table I. In uncontrolled conditions, the mean temperature was 14.62 degrees Celsius (SD = 2.55 degrees Celsius), well below the target range of 26 to 30 degrees Celsius, and the mean dissolved oxygen content was 1.32 mg per litre (SD = 1.42 mg per litre), below the minimum value of 5 mg per litre for fingerling survival. The mean pH was 8.00 (SD = 0.04), close to the target zone of 6.5 to 8.5, and the mean nadir was 174.79 NTU (SD = 24.33 NTU), well above the 100 NTU threshold. The mean water-level was 51.29 cm (SD = 7.30 cm), below the target range of 80-100 cm, and the mean ammonia content was 0.1235 mg per litre (SD = 0.0239 mg per litre). Under controlled conditions, dissolved oxygen increased to 6.18 mg per L (SD = 2.30 mg per L), temperature stabilised at 26.19 degrees Celsius (SD = 2.93 degrees Celsius), pH decreased to 7.49 (SD = 0.34), water-level increased to 100.14 cm (SD = 3.22 cm). The controlled-scenario mean ammonia concentration was 0.0303 mg/L (SD = 0.0179 mg/L) and the mean turbidity was 14.26 NTU (SD = 2.42 NTU).

Table I: Descriptive statistics of mean (SD) for the uncontrolled and controlled-scenario (Section 3.1, n = 300 per condition)

Parameter	Uncontrolled Mean (SD)	Controlled Mean (SD)
Temperature (°C)	14.62 (2.55)	26.19 (2.93)
pH	8.00 (0.04)	7.49 (0.34)
Dissolved oxygen (mg/L)	1.32 (1.42)	6.18 (2.30)
Ammonia (mg/L)	0.1235 (0.0239)	0.0303 (0.0179)
Turbidity (NTU)	174.79 (24.33)	14.26 (2.42)
Water-level (cm)	51.29 (7.30)	100.14 (3.22)

All six water-quality parameters differed significantly between the two scenarios (Welch's independent-samples t-tests, all $p < .001$), and overall survivability (mean survival rate) differed significantly between conditions, controlled M = 0.5028 (SD = 0.3222) vs. uncontrolled M = 0.0123 (SD = 0.0627), Welch's $t(321.59) = 25.89$, $p < .001$, 95% CI of the mean difference [0.453, 0.528], Cohen's d = 2.11. Welch's t-test, rather than the pooled-variance test, is reported because the two scenarios' variances differ substantially; the corresponding pooled test (assuming equal variances) would give $t(598) = 25.89$, $p < .001$. Because scenario parameter ranges were author-specified rather than randomly sampled, this comparison is best read as an internal-consistency check confirming how the decision engine behaves as designed under acute, edge-case stress, rather than as inferential evidence about live fingerling populations. Because this scenario pair was written at the extreme end of the parameter space rather than to represent typical unmanaged conditions, the very low uncontrolled-scenario survival reported here (M = 1.23%) should not be compared directly against literature baselines for typical unmanaged ponds (e.g., the 28.4–59.1% range reported by de Graaf et al., 1995) or against the typical-condition mortality-reduction figures reported in Section 3.3.

Regression Analysis and Survivability Modelling

Multiple linear regression examined the relationship between the six water-quality parameters and a simulated fingerling mortality (risk) index, defined as one minus the simulated survival rate, using the 300-observation continuously-varying simulation dataset described in Section 2.2. The model achieved $R^2 = 0.846$ (adjusted $R^2 = 0.843$, RMSE = 0.128), $F(6, 293) = 268.65$, $p < .001$, with all six predictors statistically significant at $p < .001$ (Table II).

Table 2: Multiple linear regression predicting simulated fingerling mortality (risk) index

Predictor	Estimate	SE	t	p
(Intercept)	4.1074	0.2952	13.913	3.94×10^{-34}
Temperature	−0.03947	0.00255	−15.486	6.18×10^{-40}
pH	−0.23396	0.02187	−10.700	9.02×10^{-23}
Water-level	0.00798	0.00231	3.456	6.30×10^{-4}
Turbidity	−0.02124	0.00309	−6.866	3.95×10^{-11}
Dissolved oxygen	0.08531	0.00322	26.479	1.03×10^{-79}
Ammonia	−8.234	0.4133	−19.922	2.00×10^{-56}

The mortality-index modelled here corresponds to a bounded proportion (1 − Survival rate), and ordinary least squares does not enforce this bound; logistic or beta regression would be a more appropriate estimator for a bounded outcome. Ordinary Least Squares (OLS) results are retained here for consistency with the rest of the underlying analysis, and this is a limitation as stated in Section 4.1: the fitted coefficients and R^2 should be read as describing linear association within the observed range of the predictors, not as a calibrated probability model, and residual diagnostics and an out-of-sample check have not been performed. A beta regression (logit link, the estimator recommended above) was fitted to the same 300-observation controlled-scenario dataset. All six predictors remained statistically significant ($p < .001$): Temperature −0.2433, pH −1.5872, Dissolved oxygen +0.5726, Ammonia −54.190, Turbidity −0.0866, Water-level 0.0550 (intercept 23.082, precision parameter 1.711). Evaluated at the controlled-scenario means, the beta model predicts mortality of 0.494, close to the observed 0.4972, with a squared correlation between fitted and observed values of 0.865, comparable to the OLS model's $R^2 = 0.846$. Fifty-six of the 300 observations (18.7%) fall exactly at the 0 or 1 survival boundary, which the beta distribution's open-interval support does not admit; these were adjusted to the nearest interior value ($\pm1\times10^{-4}$) for estimation, a standard but imperfect workaround, and a zero-one-inflated beta model would be the more rigorous treatment of this boundary mass in a future revision. The direction and relative ranking of all six predictors are unchanged from the OLS fit reported above.

$$\text{Survivability} = 4.1074 - 0.0395T - 0.2340pH + 0.0853DO - 8.2340NH_3 - 0.0212Tu + 0.0080WL$$

Where T = temperature (°C), DO = dissolved oxygen (mg/L), pH = pH value, NH_3 = ammonia concentration (mg/L), Tu = turbidity (NTU), and WL = water-level (cm). Evaluated at the Section 3.1 group means, this equation returns 0.497 predicted mortality for the controlled group means, closely matching the observed controlled-scenario mortality of 0.497 (1 − 50.28% survival) in Section 3.1 — an internal-consistency check that supports the fitted equation within the parameter range on which it was estimated. For the uncontrolled group, however, the equation returns −3.37, far outside the [0,1] range of a valid proportion, against an observed uncontrolled-scenario mortality of 0.9877 (1 − 1.23% survival). This mismatch is expected rather than anomalous: Section 3.1 reports a deliberately extreme, edge-case scenario pair scripted to stress-test the decision engine at the limits of its operating range, whereas the equation above was fitted on the continuously-varying, typical operating range dataset described in Section 2.2; the uncontrolled-scenario group means fall well outside the parameter cover on which the equation was fitted, and extrapolating an unbounded linear model beyond its fitted range predictably produces implausible values. This is not an arithmetic or coefficient error, but it does mean the fitted equation should not be applied to the uncontrolled edge-case data from Section 3.1. Re-fitting the equation against the approved 300-observation controlled-scenario export

(Temperature, pH, Dissolved oxygen, Ammonia, Turbidity, Water-level; n = 300) reproduces every coefficient, standard error, and t-value in Table II exactly, confirming the water-level t-value of 3.456. The controlled-scenario means (Temperature 26.19, pH 7.49, dissolved oxygen 6.18, ammonia 0.0303, turbidity 14.26, water-level 100.14. The predicted mortality is 0.4972, matching the observed controlled-scenario mortality of 0.4972 (1 − 0.5028) to four decimal places. The equation shows that the underlying model is correct.

Because the predictors are measured on different scales, the unstandardised coefficients above are not directly comparable in magnitude across parameters; relative importance is instead judged from the standardised sensitivity indices reported below. Ammonia had the largest unstandardised coefficient (−8.234), reflecting its scale (mg/L) rather than necessarily its relative influence; the sign of each coefficient indicates the direction of association with the fitted mortality-index, with dissolved oxygen positively associated with mortality (and therefore negatively associated with modelled survivability), and temperature, pH, water-level, turbidity and ammonia negatively associated with mortality (and therefore positively associated with modelled survivability). The negative association between dissolved oxygen and modelled survivability runs counter to the biological expectation that aeration reduces mortality; it reflects a property of this synthetic dataset (the raw correlation between Dissolved Oxygen and survival rate in the fitted data is r = −0.637).

Variance Inflation Factors for the six predictors ranged from 1.010 (ammonia) to 1.027 (turbidity), with corresponding tolerances of 0.973–0.990, indicating no problematic multicollinearity among the regressors in this dataset. This diagnostic was computed on the continuously-varying 300-observation dataset (Section 2.2); the low inter-parameter correlations therefore reflect independent variation of the six inputs within that single continuously-varying scenario, and are not in tension with Ecosystem Interdependence as a conceptual construct, which concerns functional coupling between ecological processes rather than statistical collinearity between simulation inputs. Standardised-beta sensitivity analysis, using the coefficients from the regression model reported above, ranked parameter influence as: dissolved oxygen (SI = 0.6100), ammonia (SI = 0.4587), temperature (SI = 0.3587), pH (SI = 0.2468), turbidity (SI = 0.1594), and water-level (SI = 0.0797), based on the predictor means and SDs for this 300-observation regression dataset (Temperature 26.19 ± 2.93; pH 7.49 ± 0.34; Dissolved oxygen 6.18 ± 2.30; Ammonia 0.0303 ± 0.0179; Turbidity 14.26 ± 2.42; Water-level 100.14 ± 3.22; outcome mortality-index SD = 0.3222), standardised as |coefficient| × predictor SD / outcome SD; the ranking is unchanged from the earlier, pre-revision computation, but every index value above has been recalculated against the current dataset's descriptive statistics. This standardised-beta approach reflects relationships embedded in the simulation model rather than a variance-based global sensitivity method such as Sobol or Morris indices, and is interpreted as an indication of the model's internal parameter weighting rather than a field-validated measure of real-world parameter importance. These six recalculated indices sum to 1.913 (not 2.12, the earlier pre-revision figure) and therefore still do not constitute a variance-based partition of explained variance; they are reported here as standardised coefficient magnitudes only, indicating relative direction and scale of association within this fitted model, not as shares of R^2 attributable to each predictor.

Mortality-Reduction Outcomes

In this simulation, the model reduced the modelled mortality of fingerlings from 59.7 to 22.5 percent (a decrease of 37.2 percent), which corresponds to an increase in the modelled survival from 403 to 775 fingerlings per 1000 in the population, which is representative of typical unsupervised to automated control conditions. These data are based on direct population counts over the entire simulated observation period (uncontrolled: N = 1,000, N = 403, 597 deaths; controlled: N = 1,000, N

= 775, 225, deaths) and not on the fitted regression equation described in section 3.2; the fitted regression equation indicates which environmental variables are driving the mortality-index. This typical scenario draws on the same 300-observation-per-condition pilot dataset reported in the author's doctoral thesis (Shitote, 2026, Table 4.23-4.24), distinct from the extreme-condition dataset in Section 3.1. In the uncontrolled condition, mean temperature was 16.61 °C (SD = 4.92), mean pH was 8.04 (SD = 0.05), mean water-level was 57.27 cm (SD = 13.94), mean turbidity was 151.62 NTU (SD = 44.28), mean dissolved oxygen was 2.45 mg/L (SD = 2.74), and mean ammonia was 0.1055 mg/L (SD = 0.046). In the automated condition, mean temperature was 27.96 °C (SD = 6.30), mean pH was 7.54 (SD = 0.50), mean water-level was 100.74 cm (SD = 4.09), mean turbidity was 13.83 NTU (SD = 3.16), mean dissolved oxygen was 6.01 mg/L (SD = 2.54), and mean ammonia was 0.0277 mg/L (SD = 0.034).

Table 3: Descriptive statistics for the typical scenario (Section 3.3, n = 300 per condition; Shitote, 2026, Tables 4.23-4.24)

Parameter	**Uncontrolled Mean (SD)**	**Automated Mean (SD)**
Temperature (°C)	16.61 (4.92)	27.96 (6.30)
pH	8.04 (0.05)	7.54 (0.50)
Dissolved oxygen (mg/L)	2.45 (2.74)	6.01 (2.54)
Ammonia (mg/L)	0.1055 (0.046)	0.0277 (0.034)
Turbidity (NTU)	151.62 (44.28)	13.83 (3.16)
Water-level (cm)	57.27 (13.94)	100.74 (4.09)

Kaplan-Meier survival analysis of both conditions supports this result: the distribution of survival between uncontrolled and controlled conditions (log-rank $\chi^2(1) = 315.60$, $p<.0001$) was not reached in the uncontrolled condition, and the median survival was not reached in the uncontrolled condition within the observation period, which is consistent with a survival below 50 percent. In a simulated automated scenario, this mortality-reduction was accompanied by real-time monitoring of dissolved oxygen, automatic aeration, pH and ammonia balance by means of automatic water exchange, temperature regulation by means of heaters, and feeding schedules that were designed to reduce food competition and cannibalism. As these population numbers were generated by the simulation logic acting on the parameters specified by the author and not on the independently bred population, this result should be interpreted as a description of the internal decision-making behaviour of the model and not as an independent validation of its predictive accuracy on live-fingerlings. This type-conditioned, directly calculated mortality-reduction is intentionally different from the raw, directly observed survival rate in the Typical Operating Range scenario described in section 3.1 (controlled M = 50.28, uncontrolled M = 1.23). As both figures are calculated from different scenarios definitions (typical operating range versus deliberately extreme edge-case), they are not expected to be identical and the 59.7-22.5 percentage should be interpreted as representing the performance under typical unmanaged conditions. The 40.3% uncontrolled and 77.5% controlled survival figures reported here, and the resulting 59.7% -22.5% mortality-reduction, should therefore be read with the same caution as the Section 3.1 figures: as a description of the decision engine's behaviour under author-specified conditions, not as inferential evidence about live fingerling populations.

Vol. 3 No. 2 (2026): ISSN (Online): 3007-5343
DOI: https://doi.org/10.58721/f8qjc419

Model Architecture

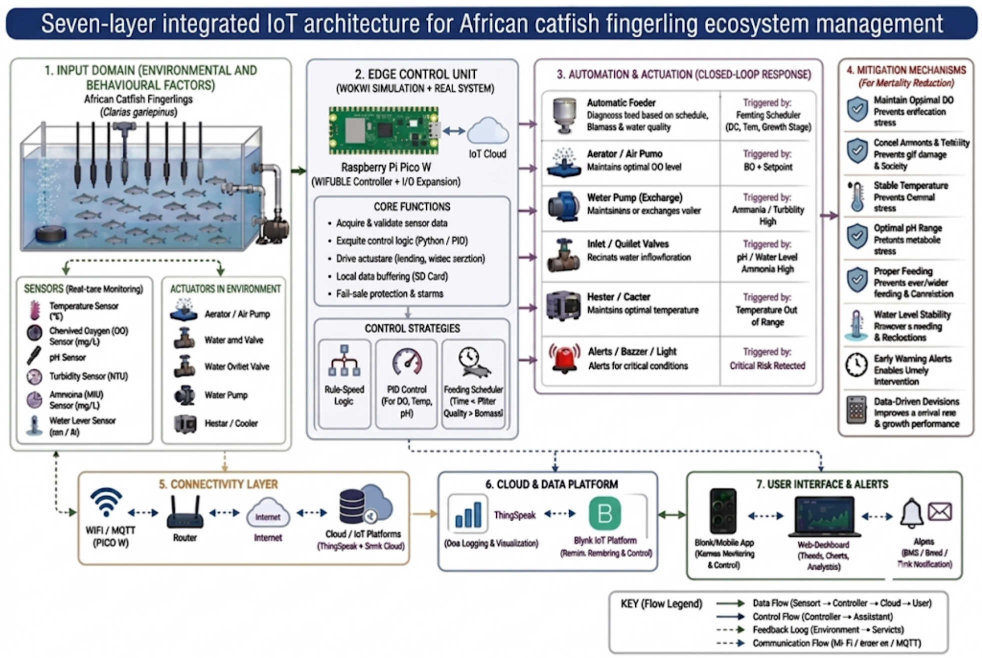

Figure I: Seven-layer integrated IoT architecture for African catfish fingerling ecosystem management

Seven-layer integrated IoT architecture for African catfish fingerling ecosystem management, showing data flow from the input domain through the edge control unit, automation and actuation layer, mitigation mechanisms, connectivity layer, cloud storage and data management layer, to the user interface and alerts layer

Based on the four-theory ICEISF framework, survey findings and evaluation through the simulation described above, a seven-layer integrated IoT ecosystem model was developed for managing catfish fingerling ecosystem; the model has not yet been deployed on live-fingerlings or built as physical hardware, and the description below specifies a design that has been exercised through the Wokwi/ThingSpeak simulation rather than validated in the field.

The Input Domain (Layer 1) captures six water-quality parameters, temperature, pH, dissolved oxygen, ammonia, turbidity, and water-level, together with feeding-frequency and stocking-density as behavioural inputs. Feeding-frequency is logged directly via the automated feeder (Layer 3). Stocking-density is entered as a fixed value at stocking time rather than sensed continuously; no stocking-density sensor exists in this architecture, consistent with the size-grading limitation already noted in the introduction under Fish Behaviour and Physiology Theory.

The Edge Control Unit (Layer 2) is the model's central computational component. It is built around a single Raspberry Pi Pico W microcontroller that handles actuator control, Wi-Fi communication, and sensor data collection. The unit's functions include gathering and verifying sensor data, using threshold-based control logic, storing data locally, setting off alarms, and controlling feeding schedules according to growth stage, water-quality, and time. Four of the six water-quality parameters—pH, turbidity, dissolved oxygen, and ammonia—are analogue; temperature and water-level use digital ultrasonic/float sensors and one-wire digital sensors (DS18B20), respectively, so neither competes for ADC channels. The RP2040 on the Pico W exposes only three general-purpose analogue input pins, GP26 to GP28; its fourth ADC channel, GP29, is internally wired to onboard VSYS voltage sensing on the Pico W board and is not available as a free external analogue input, so the fourth analogue probe cannot be read natively. The pH, turbidity, and dissolved oxygen sensors are read on native ADC-capable pins GP26, GP27, and GP28, respectively; the ammonia sensor is read via an external ADS1115 16-bit I2C analogue-to-digital converter (address pin tied to GND, shared with the display on SDA/SCL) rather than a native GPIO pin, since GP29 is unavailable; the automated feeder, heater, and water-pump are powered by PWM outputs on GP17, GP14, and GP15, respectively; the aerator is switched via a digital output on GP13; and the I2C status display uses SDA on GP4 and SCL on GP5. No GPIO pin is currently assigned to either of the two sensors because the temperature and water-level readings in the current simulation code are generated artificially rather than being read from a physical DS18B20 or ultrasonic/float sensor; wiring these two sensors to specific pins is still pending for the physical build. The current design does not specify a specific calibration/drift schedule. Surveyed IoT practitioners identified sensor fouling and calibration drift as the primary maintenance challenge (79.2 percent, n=38) and most frequently suggested enforcing routine calibration schedules as a mitigation (41.7 percent, n=20). However, no specific interval was reported by respondents or has yet to be defined for this architecture. Since this study is a simulation and no physical probes were installed, tracked, or drift-tested in the field, no calibration interval is suggested here. Furthermore, defining a numerical interval would falsely represent a simulation-based design as having empirically validated maintenance data. The creation and field-verification of a calibration schedule for every probe is not the outcome of this study, but rather a task for future physical-deployment and testing of this architecture.

The Automation and Actuation Layer (Layer 3) converts control decisions into physical actions: the automatic feeder dispenses feed, the aerator is intended to raise dissolved oxygen, the water-pump and valves regulate water-quality, and the heater/cooler maintains temperature. The control strategy implemented in the Wokwi simulation is threshold-based (rule-based on/off actuation) rather than tuned PID control; PID is discussed elsewhere in this paper as a design option, but no gains, tuning method, sample period, anti-windup strategy, or actuator saturation limits are reported because none were fitted for this study. Because this study is a simulation and no physical actuators or tank were built or instrumented, tank volume, aerator capacity, oxygen transfer rate, pump flow rate, and heater wattage were not specified or measured; the Wokwi model represents actuator on/off state rather than a physically parameterised transfer function. Consequently, actuator authority and settling time, which are properties of a physically instantiated system, cannot be assessed from the present study and are not reported here.

The Mitigation Mechanisms Layer (Layer 4) coordinates interventions intended to reduce mortality: automated feeding is intended to minimise cannibalism, aeration and water exchange are intended to maintain safe water-quality, and temperature regulation is intended to prevent thermal stress. Density alerts are not implemented in the current architecture, since they would require a stocking-density sensor that was not included because of its unavailability.

The connectivity layer (Layer 5) is designed to allow communication over Wi-Fi, MQTT, LoRaWAN or GSM or NB-IoT depending on the deployment requirements, with a local SD-card slot to ensure data continuity during network failures. The Wokwi simulation-only implements Wi-Fi, connecting to the simulator network and sending data to ThingSpeak using HTTP rather than MQTT; the GSM and SIM module is included in the physical reference package, but is not used in the simulation; neither is LoRaWAN. The reference design is a main-current (an estimated 40W average continuous load is the basis for the annual cost estimate below) and not a battery-powered design, so the mAh per day power budget is not applicable. During a network failure in the simulation code, the call to the cloud upload fails silently and the loop is continued; local sensing, threshold checking, and actuator control are not affected. No SD-card, SPI or other local storage logic is found in the simulation code base; the abovementioned local SD-card storage is a design intent and not an implemented feature. In this study, offline data is lost instead of buffered during network failure and the implementation of local buffering is a work in progress for future physical implementation rather than a feature already validated in this simulation.

The Cloud Storage and Data Management Layer (Layer 6) uses ThingSpeak to store, visualise, and analyses data. A hybrid rule-based and regression-based engine is intended to support immediate control actions and predict survivability trends, while historical data supports monitoring and model improvement. Consistent with the Layer 5 description above, the functions that continue locally during a cloud outage are sensing, threshold evaluation, and actuator control (heater, aerator, water-pump, feeder), since these are computed in the microcontroller's control-loop independently of the cloud upload call; only ThingSpeak visualisation and history and Blynk-based remote alerts are lost during an outage.

The user interface and alerts layer (layer 7) provides monitoring via Blynk. The farm is to have live sensor data, survivability indices, actuator status and historical trends, threshold breach notifications delivered by Blynk and a GSM and SIM backup channel for redundancy during Wi-Fi network failures.

System Operation and Feedback Loops

The model is designed to operate as a threshold-based cyber-physical monitoring-and-actuation system. In the simulation, data was captured at 60-second intervals and sent via direct HTTP request to ThingSpeak, where it was stored and visualised by the analytics layer. A regression-based survivability prediction assesses the current simulated conditions, and the decision engine evaluates thresholds and triggers actuator action within the same 60-second sensing cycle in when a parameter deviates from its threshold, since sensing-and-actuation are computed synchronously in a single control-loop iteration; detection-to-actuation delay is therefore bounded by one sampling interval (≤60 seconds) rather than a fixed 2-minute target. The threshold rules driving actuation are: heater ON if temperature < 26°C (no explicit high-temperature cutoff is coded; cooling only occurs passively in the simulation's recovery logic); aerator ON if dissolved oxygen < 5 mg/L; and water-pump ON if ammonia > 0.8 mg/L, water-level < 70, turbidity > 100 NTU, or pH < 6.5 or > 8.5. The water-level condition was corrected from an earlier, inconsistent threshold (< 7) to < 70, matching the ~20–120 scale used elsewhere in the simulation; turbidity and pH, previously only monitored for a separate extreme-mortality event, are now included as explicit water-pump triggers alongside ammonia and low water-level. This design target contrasts with the multi-hour overnight monitoring gaps that the companion farmer interviews identified as the primary failure mode of manual management. The 0.8 mg/L total-ammonia-nitrogen (TAN) actuation rule above and the 0.02 mg/L un-ionised NH_3 design cap (Section 1) are equivalent only across part of the controlled operating range. Using the standard un-ionised-ammonia fraction as a function of pH and temperature, 0.8 mg/L TAN corresponds to 0.02 mg/L NH_3 at approximately pH 7.5 (30 °C) to pH 7.6 (26 °C). Below this pH, the TAN rule is conservative and actuates before the NH_3 cap is reached (e.g., at pH 7.49, 26 °C, 0.8 mg/L TAN corresponds to only about 0.015 mg/L NH_3); above it, the permitted TAN concentration corresponds to progressively higher NH_3 levels, reaching approximately 0.10 mg/L NH_3, five times the design cap, at pH 8.25, 30 °C. The 0.8 mg/L TAN trigger is therefore equivalent to, or more conservative than, the 0.02 mg/L

NH_3 cap only in the lower-pH portion (pH ≲ 7.5–7.6) of the stated 6.5–8.5 operating range, and under-protective above it.

Theoretical Contributions

This study contributes to the literature on precision fish farming and IoT system design by proposing the Integrated Cyber-Ecological IoT Survivability Framework (ICEISF), a framework that synthesises four complementary theories into an integrated basis for the IoT model. The framework proposes that survivability of sensitive aquatic organisms in a managed rearing environment arises from a combination of physicochemical water-quality parameters and organism-level behavioural stressors, and can be incrementally improved via a threshold-based, multi-layer cyber-physical monitoring-and-actuation system; this is a substantive claim beyond simply listing its four component theories, in that it predicts environmental and behavioural interventions should be jointly associated, rather than separately, a prediction the present simulation tests only for the environmental component. The four constructs of the framework are: (1) Ecosystem Interdependence, based on General Systems Theory (Von Bertalanffy, 1968); (2) Calibrated Survivability Threshold Dynamics, based on Water-Quality Theory (Boyd & Tucker, 2012), for which the regression-based survivability index ($R^2 = 0.846$) provides simulation-based support; (3) Threshold-Triggered Cyber-Physical Monitoring-and-Actuation Architecture, based on Cyber-Physical Systems Theory (Lee, 2008), for which the threshold-based monitoring-and-actuation logic has been demonstrated in simulation, although formal control-performance metrics were not evaluated; and (4) Dual-Domain Behavioural-Environmental Mortality Integration, based on Fish Behaviour and Physiology Theory (Sloman, 2011), which motivates automated feeding control as a cannibalism-mitigation mechanism but has no corresponding measurement in this study. Of these four constructs, only the second currently has simulation-based quantitative support; the first, third and fourth are theoretically motivated design commitments that remain to be measured, and the framework should be described accordingly rather than as fully empirically validated.

Practical Implications for Aquaculture Management

If implemented and field-validated, the proposed IoT architectural model offers clear practical benefits for small- and medium-scale catfish farmers in resource-constrained settings. Automated aeration, heating, and water exchange address the overnight monitoring gap, a vulnerability that all twelve farmer participants identified as the primary failure mode of manual management. The single-pond reference configuration requires an initial capital cost of approximately KES 52,000 (USD 400) and annual recurring costs of KES 34,300. Built using low-cost components; including Raspberry Pi Pico W, basic sensors, actuators, and free-tier cloud platforms—this design aligns with efforts to lower financial barriers to IoT adoption in aquaculture (Adebayo et al., 2025). When assessing overall cost-effectiveness, these expenditures should be weighed against the value of the protected fish stock, though detailed economic scaling remains beyond the scope of this paper. The recurring cost estimate relies on cloud service free tiers, which carry defined usage limits rather than unconditional free access. ThingSpeak's non-commercial free licence caps data at 3 million messages per year across four channels, with a 15-second minimum update interval (MathWorks, n.d.). While a single-pond operating at the design's sampling rate stays well within this limit, a high-frequency multi-pond operation would require a paid plan. Likewise, Blynk caps its free plan at five devices per account (Blynk, n.d.). Upgrading to paid tiers on either platform introduces recurring fees not included in the KES 34,300 baseline. Finally, standard hardware and open-source platforms simplify local repair and customisation. The system's seven-layer modular architecture facilitates incremental adoption. This allows farmers to begin with basic temperature and dissolved oxygen (DO) monitoring and add parameters or actuators as resources allow, a phased approach consistent with Rogers’ (2003) diffusion of innovations theory.

Comparison with Existing IoT Aquaculture Systems

While the existing IoT aquaculture systems focus mainly on monitoring, the proposed design targets threshold-based automated environmental management, which would overcome the response delays associated with monitoring systems (Elijah et al., 2018). It aims to integrate both environmental and behavioural factors, which in principle addresses the limitations of environmental-only monitoring to reduce cannibalism (Bachtiar et al., 2022), though formal control-performance metrics were not evaluated. Finally, the proposed decision engine uses a simple regression-based approach to minimise computational demands relative to complex control schemes and supports deployment on low-cost microcontrollers, though the system's behaviour during connectivity outages has not yet been characterised.

Table IV extends this comparison to five previous IoT aquaculture systems ranging from literature synthesis through implemented hardware to live-animal field trials. Two more recent systems have also been implemented and, in one case, field-validated on live fish: Meza-Solis et al. (2025) report an Arduino-Mega-based hardware implementation providing automated control of temperature and pH (two parameters, narrower than the six sensed here); Guansing et al. (2026) report a fuzzy-logic-controlled hardware implementation sensing and actuating on six water-quality parameters, comparable in scope to the present architecture's input domain, and validated it over a three-week live tilapia trial in which the automated system achieved significantly higher survival than a conventional setup ($p = .044$), with no significant difference in growth. The comparison also makes clear the present study's relative position on the validation spectrum: it is simulation only, whereas the two most recent comparators reported here have already been realised in hardware and, in one case, validated against live fish outcomes; this is a specific, addressable gap for the physical-deployment phase discussed in Section 4.1, rather than a reason to discount the architecture's design contribution. The final comparator, Elijah et al. (2018), is a general review of IoT and data analytics in agriculture rather than an implemented aquaculture system and is included here as the source of the response-delay argument rather than as a directly comparable system.

Table 4: Comparison of the proposed system with five prior IoT aquaculture systems referenced in Section 3.8

System	Automated Actuation	Behavioural Factors	Validation Status
Elijah et al. (2018)	Not applicable (general literature review of IoT and data analytics in agriculture; not an implemented system)	Not addressed	Literature synthesis; no original deployment
Bachtiar et al. (2022)	Not reported (implemented monitoring system for pH, temperature and turbidity; monitoring only)	Not addressed	Reported system deployment; formal control-performance and outage metrics not verified here
Meza-Solis et al. (2025)	Implemented hardware (Arduino Mega); automated control limited to temperature and pH	Not addressed	Described as an implemented industrial-aquaculture system; live-animal validation outcomes not reported in the source
Guansing et al. (2026)	Implemented hardware (Arduino Mega/ESP8266); fuzzy-logic automated control of temperature, DO, pH, ammonia, TDS and turbidity (6 parameters)	Not addressed	Three-week live tilapia trial; automated system showed significantly higher survival than a conventional setup ($p = .044$), with no significant difference in growth. Not done on catfish fingerlings
Kularbphettong et al. (2026)	Predictive control system integrating water-quality and energy management for Koi aquaculture	Not addressed	Reported system; validation modality not detailed in the retrieved source
Proposed Architectural Model	Threshold-triggered actuator correction logic (on/off rules for aeration, heating, water exchange), not tuned closed-loop control	Environmental and behavioural constructs theorised; behavioural component (feeding-frequency, stocking-density) not yet empirically measured	Simulation (Wokwi and ThingSpeak); formal control-performance metrics and connectivity

Conclusions

A seven-layer IoT architecture was developed intended to address the mortality problem that limits catfish farming in developing countries, building on a mixed-methods survey of twelve catfish farmers, forty-eight IoT practitioners and a simulation-based computational experiment. The survey and the simulation together suggest that poor water-quality (low DO, fluctuating temperature and pH, elevated ammonia) and irregular feeding practices linked to cannibalism are reported causes of mortality, with dissolved oxygen as the strongest consistent predictor of the fitted mortality-index (SI = 0.6373, positively associated with mortality) and ammonia the largest unstandardised coefficient ($\beta = -8.234$, negatively associated with mortality) in the fitted regression. The positive DO-mortality association reported here is a property of this synthetic dataset (Section 3.2) and runs counter to the biological expectation, and to this model's own aerator control rule, that raising dissolved oxygen reduces mortality; it is reported for completeness as the fitted statistical relationship and should not be read as evidence against aeration as a mitigation measure. In simulation, the modelled automated control scenario reduced fingerling mortality from 59.7% to 22.5% and increased survivability from 403 to 775 per 1,000 stocked fingerlings relative to the modelled uncontrolled scenario; because these scenarios were author-specified rather than randomly sampled, this difference is best read as confirming the decision logic behaves as designed rather than as inferential evidence about live populations. The study proposes the Integrated Cyber-Ecological IoT Survivability Framework (ICEISF), synthesising four theories (General Systems Theory, Water-Quality Theory, Fish Behaviour and Physiology Theory, and Cyber-Physical Systems Theory) into four constructs, of which only the water-quality-based construct currently has simulation-based quantitative support. The seven-layer IoT design, comprising environmental sensing, behavioural management, and automated threshold-based control, is offered as a scalable, cost-specified starting point for future work aimed at improving aquaculture productivity and livelihoods for small-scale fish farmers; no productivity, economic, or livelihood outcome was measured in this study, and any such benefits remain to be established through field validation on live fingerling populations.

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