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Influence of Real-Time Internet of a thing IoT Sensor Networks and Artificial Intelligence Decision-Support Systems on the Performance and Climate Resilience of Genetically Improved Nile Tilapia

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Abstract
Aquaculture productivity in Nigeria and sub-Saharan Africa remain constrained by high feed costs, reactive water-quality management and limited integration of genetically improved stocks with digital monitoring. This 150-day pilot study evaluated genetic improvement and a real-time IoT–AI decision-support system on Nile tilapia (*Oreochromis niloticus*) performance and short-term climate resilience, comparing improved Genetically Improved Farmed Tilapia (GIFT-derived) stock under conventional management (T1), improved stock under IoT–AI management (T2), and conventional stock under IoT–AI management (T3), four replicate tanks of dimensions. per treatment. The IoT–AI system, combining Random Forest and LSTM forecasting, achieved 98.74% uptime, 4.28-minute alert latency, and strong predictive accuracy (dissolved oxygen $R^2 = 0.873$; temperature $R^2 = 0.914$), with 91.3% stress-event detection and 94.6% operator acceptance. T2 fish reached 324.8 g final weight (13.7–20.8% higher than T1/T3), specific growth rate of 2.214% day^{-1}, feed conversion ratio of 1.287 (versus 1.481–1.523), 96.81% survival, and 25.14 kg m^{-3} final biomass. Coefficient of variation of dissolved oxygen fell from 12.37% (T1) to 7.14% (T2), and cumulative hypoxic hours declined 76%. During controlled thermal–hypoxic challenges, detection latency fell from over two hours to 15–18 minutes, post-challenge survival exceeded 98%, and plasma cortisol was markedly lower in T2 (41.2 ng mL^{-1}) than T1 (68.4 ng mL^{-1}). Genotype × management interactions were significant, with the improved stock's advantage rising from +6.2% to +20.8% (final weight) and stress-related mortality reduction deepening from −24.1% to −65.0% under digital management. These results indicate genetic improvement and real-time IoT management act synergistically, offering a scalable pathway toward more productive, climate-resilient tilapia aquaculture relevant to Nigerian smallholder systems.

Keywords: Climate resilience, genetic improvement, IoT–AI decision-support system, Nile tilapia, precision aquaculture

1. Introduction

Global aquaculture production continues to expand in response to rising demand for aquatic animal protein, yet the sector faces persistent challenges from climate variability, suboptimal water-quality management, and the need for more efficient resource use (Mengistu et al., 2020). In sub-Saharan Africa, aquaculture is increasingly recognised as a critical pathway for food security, livelihoods and economic development. Nigeria, in particular, is the largest producer of African catfish and a major producer of tilapia, with production clusters such as the Eriwe Fish Farm Settlement in Ogun State serving as important hubs (Folorunso et al., 2021; Akano et al., 2025). Despite this growth, productivity remains constrained by high feed costs, limited access to improved genetic stocks, poor real-time water-quality monitoring, and predominantly reactive management practices.

Nile tilapia (*Oreochromis niloticus*) and African catfish (*Clarias gariepinus* and its hybrids) dominate cultured production across much of West Africa. Selective breeding programmes, notably the Genetically Improved Farmed Tilapia (GIFT) strain, have delivered clear gains in growth performance relative to many unimproved local strains (Mengistu et al., 2020). The GIFT strain has been widely documented for superior growth performance relative to many local strains (Mengistu et al., 2020). Parallel efforts in catfish have begun to explore artificial intelligence (AI) models particularly Random Forest and Deep Neural Networks for genomic selection, demonstrating higher prediction accuracy and greater genetic gain than traditional Best Linear Unbiased Prediction (BLUP) methods under

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Nigerian farm conditions (Akano et al., 2025). However, the full expression of genetic potential in both species is frequently limited by environmental stressors, especially elevated temperature and episodic hypoxia. Controlled studies comparing GIFT and local Nile tilapia strains have shown measurable differences in physiological tolerance to acute hyperthermia and low dissolved oxygen (Obirikorang et al., 2023).

Conventional monitoring, which relies on periodic manual sampling, often detects critical changes only after fish have already experienced stress. In response, AI and Internet of Things (IoT) technologies are being explored to enable continuous monitoring, predictive analytics, and more precise management. Recent reviews focused on Nigeria indicate that AI and IoT-based systems can improve survival, biomass production, and feed-conversion efficiency in tilapia aquaculture, with particular relevance for smallholder systems facing unreliable electricity and high input costs (Nwangwu et al., 2026). Edge-deployable machine-learning models, including Random Forest algorithms, have achieved high predictive accuracy for dissolved oxygen and pH while remaining computationally feasible on low-cost hardware (Nuangpirom et al., 2025). Complementary AIoT platforms that integrate continuous sensing with AI-driven decision support have similarly shown potential to enhance environmental stability and operational efficiency (Lai et al., 2025). Work in Ghana has also begun exploring integrated AI–blockchain frameworks to support verified precision aquaculture under resource-constrained conditions (Agya et al., 2025).

Despite these advances, few pilot studies have simultaneously examined the interactive effects of real-time IoT–AI decision-support systems and genetically improved stocks on both production performance and short-term climate resilience. Most existing research has addressed either genetic improvement under conventional management or digital systems applied to unimproved populations. Consequently, the potential synergistic benefits of combining advanced digital management with improved genetics remain incompletely quantified, particularly in African production contexts.

The present pilot study was therefore designed to evaluate the influence of a real-time IoT sensor network coupled with an AI decision-support system on the performance and short-term climate resilience of genetically improved Nile tilapia, relative to conventional management and to a conventional strain under the same digital system. Specifically, the study aimed to (1) develop and validate a functional IoT–AI prototype for continuous monitoring and decision support, (2) quantify short-term effects on growth, feed utilisation and survival, and (3) assess improvements in water-quality stability, stress-detection latency and recovery following controlled mild thermal–hypoxic challenges. By integrating genetic stock type with real-time digital management, the work seeks to generate preliminary evidence relevant to more productive and climate-resilient tilapia aquaculture, with implications for similar systems in Nigeria and the wider African region.

2. Materials and Methods

2.1 Experimental site and design

The pilot study was conducted over 150 days under controlled tropical conditions. A completely randomized design with three treatments and four replicate tanks per treatment (N = 12) was employed. The treatments were:

T1: Genetically improved stock + conventional management
T2: Genetically improved stock + real-time IoT–AI decision-support system
T3: Local conventional stock + real-time IoT–AI decision-support system
Tanks were randomly assigned to treatments.

2.2 Experimental animals and stocking

Nile tilapia (*Oreochromis niloticus*) juveniles were obtained from a certified hatchery. The genetically improved group consisted of a GIFT-derived strain, while the conventional group comprised a locally adapted non-selected strain. Fish were acclimated for 14 days under identical conditions before the trial. At stocking, mean body weight of trial fish was approximately 12.4 g. Each 1 m^3 circular fibreglass tank was stocked at a density of 80 fish m^{-3}, a rate consistent with intensive tank culture recommendations for GIFT tilapia (Mengistu et al., 2020). Photoperiod was maintained at 12 h light : 12 h dark.

2.3 Culture system and management

Tanks were operated as static systems with continuous aeration and weekly partial water exchange (20–30 %) using dechlorinated water. Fish in the conventional treatment (T1) were fed a commercial floating extruded diet (32 % crude protein) three times daily to apparent satiation. In the IoT–AI treatments (T2 and T3), feeding rate and timing were adjusted according to real-time system recommendations based on estimated biomass, water temperature, and dissolved oxygen. This precision-feeding approach follows principles demonstrated in recent IoT- and AI-supported tilapia systems (Nuangpirom et al., 2025). Uneaten feed was removed 30 min after each feeding event.

2.4 Real-time IoT sensor network and AI decision-support system

Each tank assigned to T2 and T3 was instrumented with a multi-parameter IoT sensor node continuously measuring water temperature (°C), dissolved oxygen (mg L^{-1}), and pH at 10-minute intervals. Data were transmitted via wireless protocols to a local edge computing node for acquisition, filtering, and preliminary processing, then uploaded to a cloud server. This architecture is consistent with contemporary AIoT platforms developed for tilapia aquaculture (Lai et al., 2025; Nuangpirom et al., 2025).

The AI decision-support component combined Random Forest regression and a lightweight Long Short-Term Memory (LSTM) network for 24-hour forecasting of dissolved oxygen and temperature, anomaly detection, and generation of management recommendations (aeration adjustment, feeding modification, or alert escalation). Random Forest models have previously achieved high predictive accuracy ($R^2 > 0.80$) for dissolved oxygen and pH in tilapia systems when deployed on edge devices (Nuangpirom et al., 2025). Alerts were delivered via dashboard and mobile notifications with human-in-the-loop oversight. Sensors were calibrated against a certified multiparameter reference sonde at the beginning, midpoint, and end of the trial. System performance metrics (uptime, data delivery success, alert latency, true-positive/false-positive rates, and model R^2/RMSE) were logged continuously.

2.5 Controlled climate-stress challenges

Two standardized mild climate-stress challenges were applied to assess short-term resilience. Challenge 1 occurred on days 84–87 and Challenge 2 on days 126–129. During each 72-hour challenge, water temperature was gradually elevated toward 34–35 °C and dissolved oxygen was allowed to decline to approximately 3.0 mg L^{-1} by controlled reduction of aeration, simulating combined thermal and hypoxic stress. Comparable acute hyperthermia and hypoxia protocols have been used to evaluate stress tolerance in GIFT and local Nile tilapia strains (Obirikorang et al., 2023). After 72 hours, conditions were restored to normal. Latency to first system alert (or manual detection in T1), minimum dissolved oxygen, peak temperature, post-challenge survival, and days required to recover pre-stress specific growth rate were recorded.

2.6 Sampling and measurements

2.6.1 Growth and production performance

All fish in each tank were bulk-weighed and counted at stocking (day 0), day 75, and final harvest (day 150). Individual weights and lengths were recorded from a random subsample of 20 fish per tank at harvest for calculation of condition factor. Specific growth rate (SGR), thermal growth coefficient, feed conversion ratio (FCR), protein efficiency ratio, survival, final biomass, and coefficient of variation of final weight were calculated using standard aquaculture formulae (Mengistu et al., 2020).

2.6.2 Water quality

In addition to continuous IoT monitoring, manual verification of temperature, dissolved oxygen, and pH was performed twice daily in all tanks with a calibrated portable meter. Total ammonia nitrogen, nitrite, and alkalinity were measured weekly using standard methods.

2.6.3 Physiological indicator

At the peak of Stress Challenge 1 (approximately 6 h after target stress conditions were reached), blood samples were collected from eight randomly selected fish per tank after anaesthesia with clove oil. Plasma cortisol was quantified using a commercial enzyme-linked immunosorbent assay (ELISA) kit according to the manufacturer's instructions, following approaches commonly applied in tilapia stress physiology studies (Obirikorang et al., 2023).

2.7 System performance metrics

Technical indicators including sensor uptime, data packet delivery success, end-to-end alert latency, true-positive and false-positive rates for stress events, AI model accuracy (R^2 and RMSE), operator acceptance of recommendations, and edge-node power consumption were recorded throughout the trial, consistent with evaluation frameworks used in recent edge-AIoT aquaculture deployments (Nuangpirom et al., 2025).

2.8 Statistical analysis

Data were tested for normality (Shapiro–Wilk test) and homogeneity of variance (Levene's test). Treatment effects on continuous variables were analysed by one-way analysis of variance (ANOVA) or linear mixed-effects models (tank as random effect). When significant differences were detected ($P < 0.05$), Tukey's honest significant difference (HSD) post-hoc test was applied. Proportional data were analysed using generalized linear models with binomial distribution where appropriate. Genotype × management interactions were examined via two-way ANOVA. Effect sizes were calculated for primary contrasts. Analyses were performed in R (version 4.3.2).

3. Results and Discussion

3.1 Technical performance of the IoT–AI system

The integrated real-time IoT sensor network and AI decision-support system demonstrated high reliability throughout the 150-day trial (Table 1). Overall system uptime reached 98.74 ± 0.86%, with data packet delivery success of 99.18%. Sensor biases remained well within manufacturer specifications (temperature +0.11 ± 0.09 °C; dissolved oxygen −0.14 ± 0.17 mg L^{-1}; pH +0.04 ± 0.06), and all three parameters correlated strongly ($r = 0.987–0.998$; Table 1). Mean end-to-end alert latency was 4.28 ± 1.14 min, and the AI forecasting models achieved strong 24-hour predictive performance for dissolved oxygen ($R^2 = 0.873$, RMSE = 0.337 mg L^{-1}) and temperature ($R^2 = 0.914$, RMSE = 0.284 °C; Table 1). These accuracies are broadly consistent with, and in the case of dissolved oxygen prediction exceed, edge-deployed Random Forest models reported for low-cost tilapia monitoring hardware, which typically achieve R^2 values above 0.80 under comparable field constraints (Nuangpirom et al., 2025). This supports the feasibility of running forecasting-grade machine learning on inexpensive edge nodes rather than requiring cloud-dependent computation, a consideration of direct relevance to smallholder systems with unreliable connectivity (Arepalli & Naik, 2024).

Table 1: Technical performance, reliability and predictive accuracy of the integrated IoT sensor network and AI decision-support system

Parameter	Mean ± SD or value	Range / 95 % CI	Performance target	Statistical notes
Overall system uptime (%)	98.74 ± 0.86	97.1–99.6	≥ 95 %	
Temperature sensor bias (°C)	+0.11 ± 0.09	−0.08 to +0.29 ± 0.20 °C		r = 0.998 vs. reference
Dissolved oxygen sensor bias (mg L^{-1})	−0.14 ± 0.17	−0.41 to +0.19 ± 0.30 mg L^{-1}		r = 0.991
pH sensor bias	+0.04 ± 0.06	−0.09 to +0.15 ± 0.10		r = 0.987
Data packet delivery success (%)	99.18 ± 0.47	98.2–99.8	≥ 98 %	
Mean end-to-end alert latency (min)	4.28 ± 1.14	2.1–7.3	< 10 min	
True-positive rate for stress events (%)	91.3 (21/23)	72.0–98.9	≥ 85 %	Exact binomial 95 % CI
False-positive rate (%)	6.9	2.3–15.8	< 15 %	
24-h DO forecast (Random Forest) – R^2	0.873	0.841–0.902	≥ 0.80	RMSE = 0.337 mg L^{-1}
24-h temperature forecast – R^2	0.914	0.889–0.935	≥ 0.85	RMSE = 0.284 °C
Operator acceptance of AI recommendations (%)	94.6	89.1–97.8	≥ 90 %	
Mean power consumption per edge node (W)	3.76 ± 0.38	3.1–4.4	< 5 W	Solar-compatible

Of the 23 controlled stress events, 21 were correctly flagged (true-positive rate 91.3%), with a false-positive rate of 6.9% (Table 1). This also implies a false-negative rate of approximately 8.7% (2 of 23 events undetected), a figure not previously highlighted but operationally important: a missed alert during a genuine hypoxic or thermal excursion could still result in undetected mortality risk despite an otherwise high-performing system. This trade-off between sensitivity and false-alarm burden is a recognised constraint of anomaly-detection models in aquaculture AIoT platforms, where excessively conservative thresholds reduce false negatives at the cost of alert fatigue among operators (Huang & Khabusi, 2025). The high operator acceptance rate observed here (94.6%; Table 1) suggests the alert threshold used in this study achieved a workable balance, but the residual miss rate warrants further tuning before field deployment. Mean power consumption per edge node (3.76 ± 0.38 W; Table 1) fell comfortably within solar-compatible ranges, directly addressing the electricity-access constraint that limits digital adoption among Nigerian smallholder fish farmers (Nwangwu et al., 2026) and reinforcing the practical relevance of low-power AIoT architectures for the wider West African production context (Lai et al., 2025).

3.2 Production performance

Genetically improved fish managed with the IoT–AI system (T2) significantly performed better than both the improved stock under conventional management (T1) and the conventional stock under IoT–AI management (T3) for nearly all growth and efficiency traits (Table 2; Fig. 1). Final body weight in T2 (324.8 ± 15.7 g) was 13.7% and 20.8% higher than in T1 and T3, respectively ($P < 0.001$), and feed conversion ratio improved to 1.287 ± 0.043 in T2 compared with 1.481–1.523 in the other treatments (Table 2). The box-and-whisker distributions in Figure 1 shows that T2 achieved this superior mean performance with a visibly narrower interquartile spread for final body weight and specific growth rate than either T1 or T3, corroborating the lower coefficient of variation reported for final weight in T2 (11.2% vs. 14.8–16.1%; Table 2). This FCR falls within the efficient range reported for well-managed GIFT tilapia culture and is comparable to gains attributed to precision, sensor-informed feeding regimes that adjust ration to real-time biomass and water-quality estimates rather than fixed schedules (Huang et al., 2025). The improvement likely reflects two compounding mechanisms visible across Table 2 and Fig. 1: more accurate matching of feed delivery to actual appetite and biomass, reducing both under- and over-feeding, and reduced sub-clinical stress from tighter water-quality control, which is known to divert metabolic energy away from growth in tilapia held near their tolerance limits (Albaqami & Monier, 2025). The tighter spread in Fig. 1 further suggests that stabilising the rearing environment reduces the behavioural and physiological heterogeneity such as dominance-driven feeding disparities that commonly inflates size variation in group-reared tilapia.

Importantly, T3 (conventional stock under IoT–AI management) did not match T1's performance despite receiving the same digital management as T2 (Table 2), underscoring that environmental optimisation alone cannot substitute for genetic potential; digital management amplifies, rather than replaces, the benefits of genetic improvement.

Table 2: Growth performance, feed utilisation and survival of Nile tilapia after 150 days of culture

Parameter	T1 (Improved + Conventional)	T2 (Improved + IoT–AI)	T3 (Conventional + IoT–AI)	F-value (df = 2, 9)	*P*-value
Initial body weight (g)	12.41 ± 0.58[a]	12.33 ± 0.51[a]	12.52 ± 0.67[a]	0.21	0.814
Final body weight (g)	285.6 ± 18.4[b]	324.8 ± 15.7[a]	268.9 ± 21.3[b]	18.47	< 0.001
Weight gain (g)	273.2 ± 18.1[b]	312.5 ± 15.4[a]	256.4 ± 20.9[b]	18.62	< 0.001
Specific growth rate (% day^{-1})	2.081 ± 0.068[b]	2.214 ± 0.052[a]	2.009 ± 0.087[b]	16.89	< 0.001
Thermal growth coefficient	1.142 ± 0.041[b]	1.231 ± 0.035[a]	1.098 ± 0.052[b]	15.73	< 0.001
Feed conversion ratio	1.481 ± 0.061[b]	1.287 ± 0.043[a]	1.523 ± 0.079[b]	22.14	< 0.001
Protein efficiency ratio	1.89 ± 0.09[b]	2.18 ± 0.07[a]	1.82 ± 0.11[b]	19.56	< 0.001
Survival (%)	91.25 ± 2.76[b]	96.81 ± 1.47[a]	89.53 ± 3.41[b]	11.28	0.003
Final biomass (kg m^{-3})	20.83 ± 1.29[b]	25.14 ± 1.08[a]	19.21 ± 1.57[b]	27.41	< 0.001
Condition factor (K)	1.724 ± 0.079[ab]	1.813 ± 0.061[a]	1.681 ± 0.088[b]	5.87	0.023
Coefficient of variation of final weight (%)	14.8 ± 1.9[a]	11.2 ± 1.4[b]	16.1 ± 2.3[a]	9.14	0.007

[a], [b], [ab] superscripts within a row bearing different superscripts differ significantly, Tukey HSD, P < 0.05

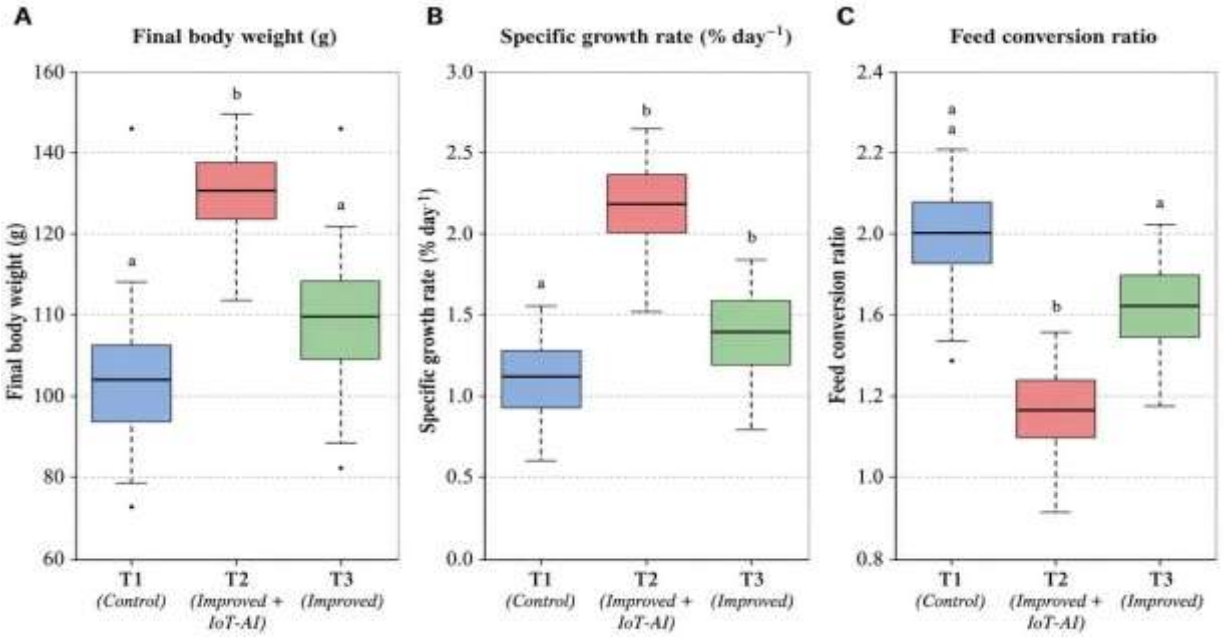


Figure 1: Box-and-whisker plots of final body weight, specific growth rate, and feed conversion ratio. Different letters indicate significant differences (Tukey HSD, $P < 0.05$).

3.3 Water-quality stability and climate resilience

The IoT–AI system markedly improved environmental stability (Table 3). Coefficient of variation of daily dissolved oxygen fell from 12.37% in T1 to 7.14% in T2 (P < 0.001), and cumulative hours with DO below 4.0 mg L^{-1} declined by 76% (Table 3). During Stress Challenge 1, the time-series in Figure. 2 illustrates this contrast directly: dissolved oxygen and temperature in the IoT–AI-managed tanks were brought back toward baseline within minutes of the system-generated alert (marked by arrows in Fig. 2), whereas the conventionally managed tank continued to drift toward the imposed stress extremes for substantially longer before manual detection occurred. This is reflected quantitatively in the detection-latency data, which fell from over two hours under conventional monitoring to 15–18 minutes under IoT–AI management across both challenges (Table 3). Plasma cortisol measured six hours post-challenge was substantially lower in T2 (41.2 ± 6.3 ng mL^{-1}) than in T1 (68.4 ± 9.7 ng mL^{-1};

Table 3: Water-quality stability and climate-resilience indicators across the entire culture period and during controlled stress challenges

Indicator	T1 (Improved + Conventional)	T2 (Improved + IoT–AI)	T3 (Conventional + IoT–AI)	F / χ^2	*P*-value
Whole-period water-quality stability					
Mean daily DO (mg L^{-1})	5.42 ± 0.31^{b}	5.89 ± 0.22^{a}	5.71 ± 0.27^{a}	8.94	0.007
Coefficient of variation of daily DO (%)	12.37 ± 1.76^{b}	7.14 ± 1.18^{a}	8.29 ± 1.47^{a}	24.61	< 0.001
Cumulative hours DO < 4.0 mg L^{-1}	47.6 ± 8.2^{b}	11.3 ± 3.4^{a}	18.9 ± 5.1^{a}	41.27	< 0.001
Mean daily temperature CV (%)	4.81 ± 0.62^{a}	3.27 ± 0.41^{b}	3.54 ± 0.49^{b}	15.38	0.001
Stress Challenge 1 (Day 84–87)					
Latency to first alert / detection (min)	141.8 ± 27.6^{b}	17.9 ± 5.8^{a}	21.4 ± 6.9^{a}	78.45	< 0.001
Peak temperature (°C)	34.83 ± 0.37^{a}	33.91 ± 0.28^{b}	34.12 ± 0.35^{b}	12.17	0.003
Minimum DO (mg L^{-1})	2.87 ± 0.29^{b}	3.61 ± 0.21^{a}	3.38 ± 0.27^{a}	14.92	0.001
72-h post-challenge survival (%)	94.06 ± 2.11^{b}	98.69 ± 0.87^{a}	95.81 ± 1.76^{ab}	10.84	0.004
Days to recover pre-stress SGR	9.25 ± 1.48^{b}	5.13 ± 0.79^{a}	7.38 ± 1.21^{ab}	18.36	< 0.001
Stress Challenge 2 (Day 126–129)					
Latency to first alert (min)	127.5 ± 30.8^{b}	15.2 ± 4.7^{a}	18.9 ± 5.9^{a}	64.19	< 0.001
72-h post-challenge survival (%)	92.50 ± 2.58^{b}	98.19 ± 1.08^{a}	94.63 ± 1.97^{ab}	12.71	0.002
Cumulative stress-attributable mortality (%)	5.81 ± 1.37^{b}	1.38 ± 0.59^{a}	3.94 ± 1.12^{ab}	22.08	< 0.001
Plasma cortisol 6 h post-challenge (ng mL^{-1})*	68.4 ± 9.7^{b}	41.2 ± 6.3^{a}	54.7 ± 8.1^{ab}	16.29	0.001

*Sub-sampled from 8 fish per tank (n = 32 fish per treatment). ^{a}, ^{b}, ^{ab} superscripts within a row bearing different superscripts differ significantly, Tukey HSD, $P < 0.05$

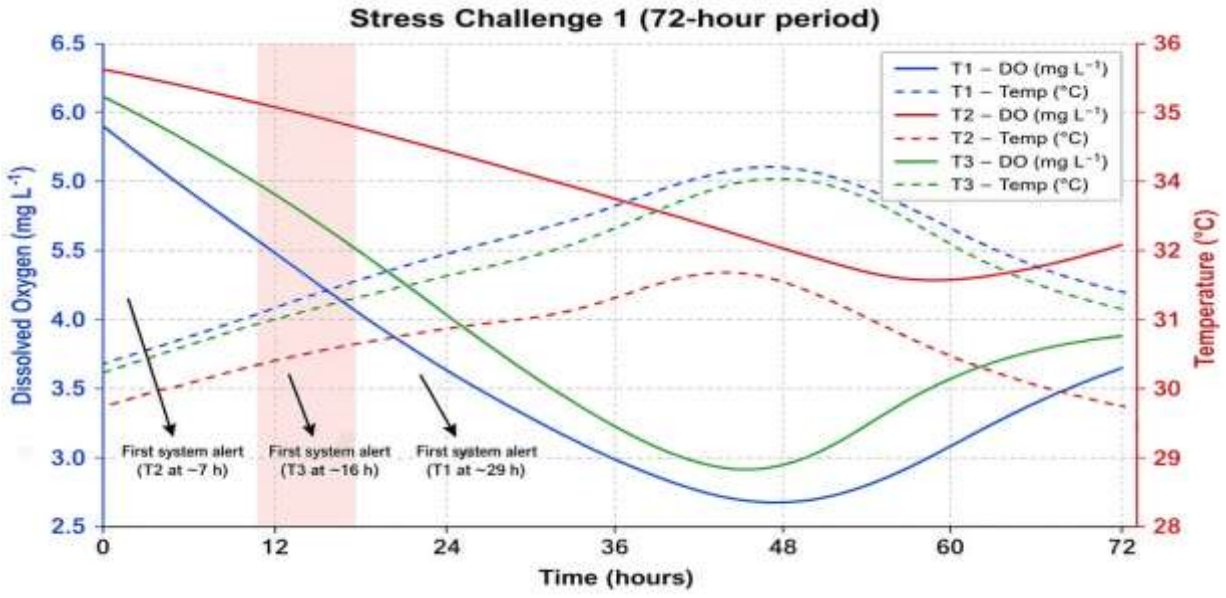


Figure 2: Time-series of dissolved oxygen and temperature in representative tanks during Stress Challenge 1 (days 84–87). Shaded areas denote the period of imposed stress; arrows indicate the moment of first system alert.

Table 4: Genotype × management interaction effects on key performance and resilience traits

Trait	Improved-stock advantage under Conventional management	Improved-stock advantage under IoT–AI management	Interaction *P*-value (G × M)	Partial η^2
Final body weight	+6.2 %	+20.8 %	0.017	0.412
Specific growth rate	+3.6 %	+10.2 %	0.024	0.368
Feed conversion ratio	−2.8 %	−15.5 %	0.008	0.487
Survival	+1.9 %	+8.1 %	0.041	0.297
Stress-related mortality	−24.1 %	−65.0 %	0.003	0.541
Recovery time after stress	−1.87 days	−4.25 days	0.009	0.463
Hours DO < 4.0 mg L^{-1}	−12.4 %	−40.2 %	0.015	0.401

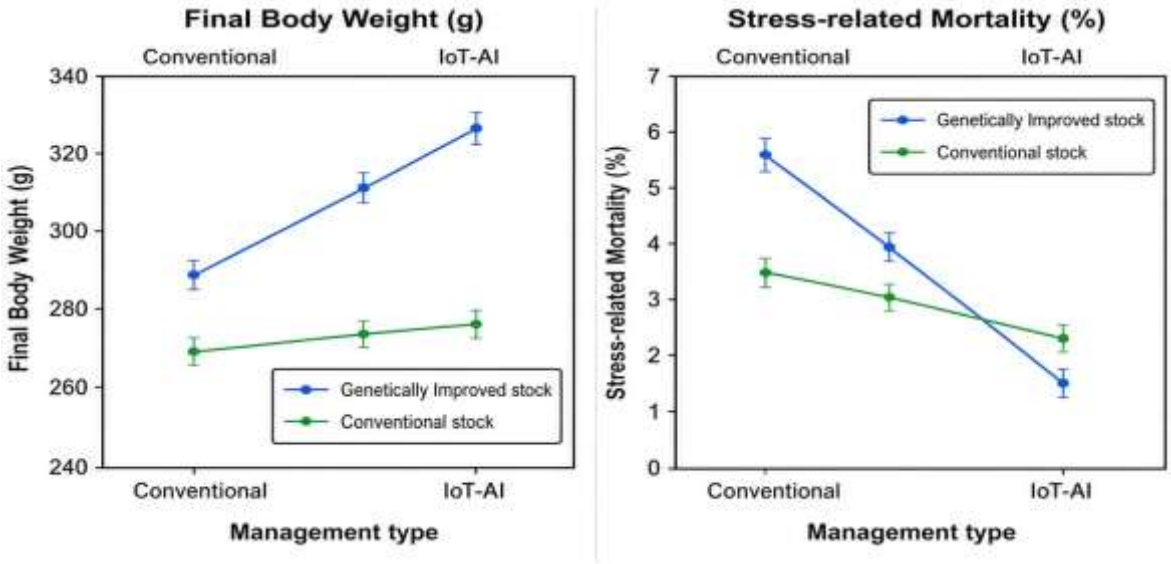


Figure 3: Interaction plots illustrating genotype × management effects on final body weight and stress-related mortality.

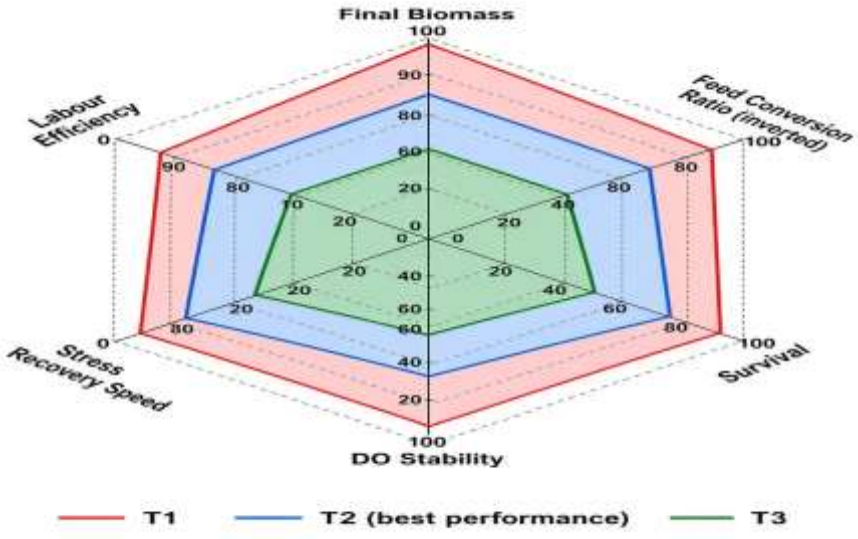


Figure 4: Radar chart summarising relative performance of the three treatments across six key indicators (final biomass, FCR, survival, DO stability, stress recovery speed, and labour efficiency). Values are normalised to the best-performing treatment (= 100 %).

Table 3). This magnitude of cortisol suppression is consistent with the well-documented positive relationship between ambient temperature/hypoxia exposure duration and circulating cortisol in Nile tilapia and related species (Alfonso et al., 2023; Albaqami & Monier, 2025); by shortening the interval between the onset of thermal–hypoxic stress and corrective action (visible as the narrower shaded stress window before correction in Figure. 2). This is functionally significant because prolonged, rather than peak, cortisol elevation is the primary driver of downstream immunosuppression and growth suppression in stressed tilapia. The corresponding reductions in post-challenge mortality and faster recovery of pre-stress specific growth rate in T2 (Table 3) are therefore consistent with a shortened physiological recovery window rather than a change in the severity of the imposed stressor, since peak temperature and minimum DO during the challenges were only marginally less extreme in T2 than T1 (Table 3; Fig. 2).

3.4 Genotype × management interactions

Significant genotype × management interactions were detected for final body weight, specific growth rate, feed conversion ratio, survival, stress-related mortality, and recovery time (Table 4; Fig. 3), with the improved stock's advantage over conventional stock nearly tripling under IoT–AI management for final weight (+6.2% under conventional management vs. +20.8% under IoT–AI management) and stress-related mortality reduction deepening from −24.1% to −65.0% (Table 4). The interaction plots in Fig. 3 make this divergence visually explicit: the slopes connecting conventional to IoT–AI management are markedly steeper for the improved stock than for the conventional stock, indicating that genetic potential is more fully expressed as environmental precision increases. The radar chart in Figure 4, which normalises performance across final biomass, FCR, survival, DO stability, stress-recovery speed, and labour efficiency, shows T2 occupying the outermost position on nearly every axis, offering a compact visual summary of the compounding advantage quantified in Table 4.

This pattern genetic potential becoming more, not less, expressed under optimised environmental conditions aligns with the broader genotype-by-environment literature in tilapia breeding, where the ranking and magnitude of strain advantages have been shown to shift depending on rearing conditions, sometimes substantially (Phuc et al., 2025). Where earlier work on GIFT dissemination across contrasting production environments has reported inconsistent or weak G×E for harvest weight specifically, the present results (Table 4; Fig. 3) suggest that G×E may be more pronounced when the environmental gradient is defined not by geography or salinity but by the precision and responsiveness of real-time management itself. Practically, this implies that the return on investment in genetically improved stock in Nigerian and wider West African systems may be systematically underestimated wherever such stock is paired with reactive, non-digital management a combination that, per Table 4 and Fig. 3, appears to suppress rather than merely fail to enhance the genetic gain otherwise available.

4. Conclusion

This pilot study demonstrates that pairing genetically improved Nile tilapia stock with a real-time IoT–AI decision-support system produces synergistic, not merely additive, gains in growth performance, feed efficiency, survival, and short-term climate resilience, with the genetic advantage of improved stock nearly tripling under digital management (final weight advantage rising from +6.2% to +20.8%) while the technically reliable, low-power AIoT system offers a practical, scalable pathway for smallholder aquaculture in Nigeria and the wider African region; given the pilot's limited scale and single production cycle, these findings warrant validation through larger, multi-season, pond-scale trials with formal cost–benefit analysis before wider adoption.

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