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# Integrating IoT Data and Consumer Behavior Analytics to Enhance Decision-Making in Sustainable Koi Fish Cultivation

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ABSTRACT

This study presents a data-driven decision-support framework that integrates Internet of Things (IoT)–based water quality monitoring with consumer behavior analytics to support sustainable koi fish cultivation. An IoT monitoring system was implemented using an ESP32 microcontroller equipped with pH, dissolved oxygen (DO), temperature, and turbidity sensors to continuously record water quality conditions over a 30-hour observation period. Time-series sensor data were processed through noise filtering, timestamp synchronization, and descriptive statistical analysis to characterize environmental stability patterns. In parallel, consumer behavior data were collected from 50 respondents using an online questionnaire addressing color preference, purchase considerations, maintenance awareness, and price sensitivity. The integrated analysis combined correlation analysis and K-Means clustering to explore relationships between water quality stability indicators and consumer segmentation. The results indicate that relatively stable pH (6.66–7.20) and DO (6.0–7.1 mg/L) conditions align with the preferences of quality-focused and maintenance-oriented consumer groups, while automated IoT-based monitoring supports operational efficiency relevant to budget-conscious buyers. Overall, the findings demonstrate that integrating environmental sensing data with consumer behavior analytics can enhance operational decision-making, improve market alignment, and support sustainability in koi aquaculture systems.

## INTRODUCTION

Koi fish cultivation has emerged as one of the most valuable sectors within Indonesia's ornamental aquaculture industry, driven by increasing consumer demand for aesthetically appealing and high-quality koi fish. The economic potential of this industry is strongly influenced by environmental stability, particularly water quality, which directly affects koi coloration, growth performance, immune response, and overall market value. Critical parameters such as pH, dissolved oxygen (DO), temperature, and turbidity must be continuously maintained within optimal thresholds. However, fluctuations in these parameters often occur unpredictably and may lead to physiological stress, susceptibility to disease, or mortality, resulting in financial losses for farmers and breeders.

Recent technological advancements, particularly in the field of the Internet of Things (IoT), have enabled automated and real-time environmental monitoring as a solution to these challenges [1], [2]. IoT-based water quality monitoring allows continuous data acquisition from multiple sensors, early detection of harmful parameter deviations, and rapid decision-making. Despite these advantages, current IoT implementations in aquaculture predominantly focus on environmental sensing alone [3], [4]. Decision-making processes remain limited because they do not incorporate broader contextual insights, such as consumer purchasing trends, perception of fish quality, or preferences related to color patterns, size, health, and maintenance practices. As a result, many farmers still make operational and business decisions using traditional intuition-based approaches that may not align with actual market behavior.

In parallel, the field of consumer behavior analytics has shown significant potential in improving strategic decision-making across various industries [5]. For koi fish cultivation, understanding consumer preferences such as desired coloration intensity, willingness to pay, brand perception, and maintenance awareness can play a central role in aligning production strategies with market expectations. Yet, to date, the integration of consumer behavior insights with IoT-based aquaculture data remains largely unexplored, leaving a substantial research gap in the development of holistic decision-support systems for sustainable koi farming [6].

This study addresses this gap by proposing an integrated analytical framework that combines IoT-derived water quality data with consumer behavior analytics. By correlating environmental fluctuations with consumer preferences and purchasing tendencies, the framework aims to generate more informed operational decisions, enhance sustainability, and strengthen business performance. Furthermore, the integration offers a new perspective on how data-driven models can help breeders optimize cultivation practices not only for biological outcomes but also for market responsiveness [7]. This research contributes to the growing body of smart aquaculture systems by demonstrating a multidimensional decision-making approach that leverages both technological and behavioral datasets to support sustainable koi fish cultivation in Indonesia.

Research on IoT-based aquaculture has grown substantially in the last decade, with a primary focus on environmental monitoring, automated control, and predictive maintenance. Early studies such as [1] developed systems integrating pH, temperature, and dissolved oxygen (DO) sensors to maintain optimal water conditions for freshwater species. These works demonstrate that continuous monitoring significantly reduces fish mortality rates by detecting anomalies earlier than manual observation [2]. Subsequent research expanded sensor modalities such as turbidity , ammonia detection , and water-level sensing which enabled more robust decision-making in intensive aquaculture [8].

More advanced approaches introduced machine learning models for forecasting water quality patterns. Studies implemented time-series prediction (e.g., LSTM, ARIMA) to anticipate abrupt environmental shifts, allowing farmers to perform proactive aeration or water replacement. Other research explored automated control systems coupled with IoT platforms, such as smart aeration and adaptive feeding systems [9], [10]. These solutions aimed to improve operational efficiency while reducing labor intensity. However, these works predominantly emphasize biophysical and environmental parameters, with little consideration for economic or behavioral factors. In parallel, consumer behavior research has gained traction in the ornamental fish industry [5], though often independently from technological monitoring systems. Prior studies [6] examined purchasing preferences based on fish coloration, pattern uniqueness, growth potential, and price elasticity. Additionally, analyzed market segmentation of ornamental fish buyers, identifying groups such as hobbyists, collectors, and commercial resellers. These studies indicate that consumer preferences play a substantial role in determining cultivation strategies, including selective breeding, marketing, and maintenance investment.

Despite the importance of both domains, research integrating IoT-based aquaculture monitoring with consumer behavior analytics remains limited. Most IoT studies treat cultivation purely as a biological optimization problem, while market studies analyze consumer patterns without real-time operational data [11] . This disconnect limits the ability of koi farmers to make decisions that balance environmental conditions, fish health, and market demand. As highlighted by [1] , ornamental aquaculture requires a multidimensional approach that accounts not only for ecological parameters but also for consumer-driven value creation.

To address this gap, the present study proposes an integrated framework combining sensor-generated water quality data with consumer behavior analytics, enabling more comprehensive decision support. By linking environmental performance with market-driven insights, this research contributes to the development of sustainable koi cultivation models that optimize both biological outcomes and business strategies.

## METHOD

This study integrates IoT-based water quality monitoring with consumer behavior analytics to develop a data-driven decision-support framework for sustainable koi fish cultivation. The methodological workflow consists of four primary stages: data acquisition, transmission, analytics, and decision support, as illustrated in Figure 1. This structure enables systematic integration between real-time environmental sensing and behavioral data analysis.

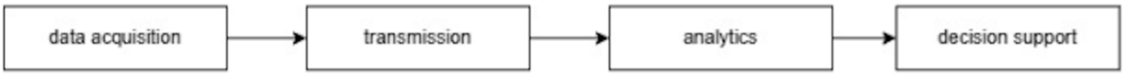


Figure 1. Research Method Process

### Experimental Setup and IoT System Design

A controlled outdoor koi pond located in Mojokerto, Indonesia, was used as the primary experimental site. The pond has an approximate water capacity of 2,000 liters with a depth ranging from 10 to 15 cm, representing small- to medium-scale koi farming conditions. An ESP32 microcontroller was utilized as the central data acquisition node due to its low power consumption and integrated Wi-Fi connectivity [12]. The developed IoT system was equipped with four water quality sensors: a pH sensor (E-201 type) to measure acidity levels, a dissolved oxygen (DO) probe to evaluate oxygen availability, a DS18B20 temperature sensor to monitor thermal stability, and a turbidity sensor (SKU SEN0189) to detect suspended particles and water clarity. All sensors were calibrated prior to deployment to minimize measurement drift and ensure data reliability.

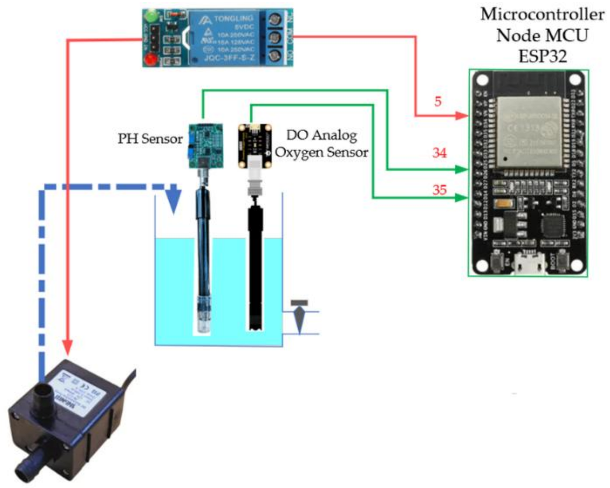


Figure 2. Reference architecture and representative components of an IoT-based water quality monitoring system used for koi fish cultivation

Sampling was performed at 30-second intervals, and the ESP32 transmitted real-time sensor readings to a cloud-based IoT platform using Firebase and Blynk services. The collected data were stored for historical analysis and visualized through a web-based dashboard. The dashboard interface enabled real-time monitoring of parameter trends, detection of threshold violations, and early warning alerts to support timely decision-making by koi farmers. Figures 2 illustrating the IoT system architecture and hardware components are presented for reference purposes to depict the functional configuration of the implemented system.

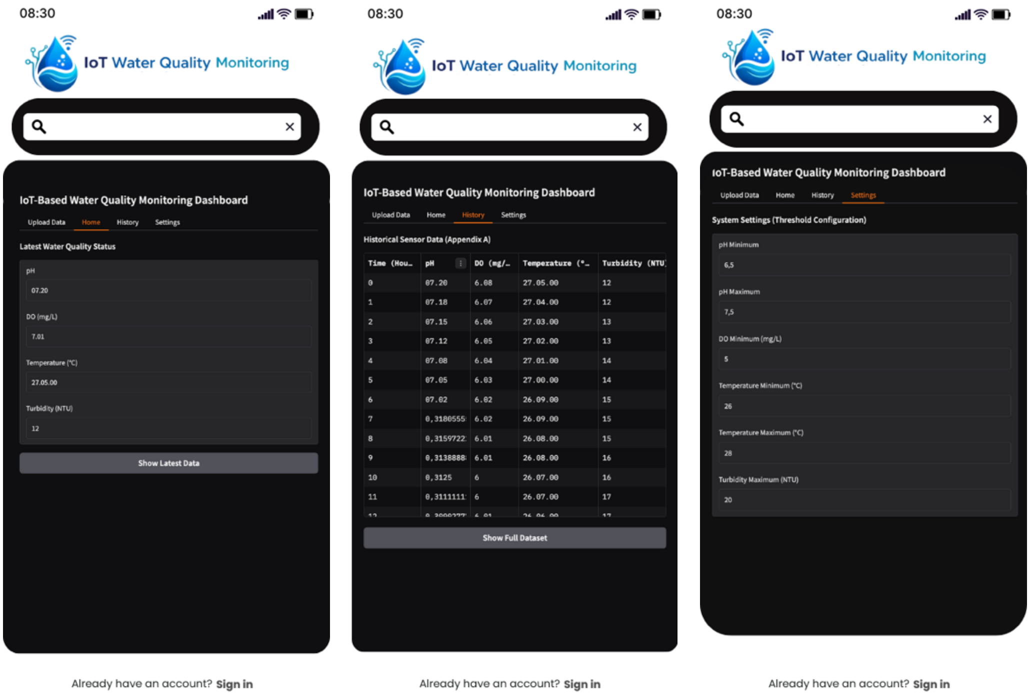


Figure 3. Dashboard illustrating (a) real-time water quality monitoring, (b) historical sensor data visualization, and (c) system settings for threshold configuration and decision support.

Figure 3 presents a dashboard of the proposed IoT-based water quality monitoring system. Figure 3(a) displays the real-time monitoring interface, which provides the latest measurements of key water quality parameters, including pH, dissolved oxygen, temperature, and turbidity, enabling farmers to quickly assess current pond conditions. Figure 3(b) illustrates the historical data visualization module, where time-series sensor records are presented in tabular form to support trend analysis and retrospective evaluation of environmental stability. Figure 3(c) shows the system settings interface, which allows users to configure parameter thresholds and monitoring limits, supporting early warning detection and data-driven decision support for sustainable koi fish cultivation.

**Water Quality Data Collection and Processing**

Water quality data were recorded continuously throughout the experimental period. To ensure analytical consistency, the raw sensor readings underwent several preprocessing steps before analysis. Noise filtering was applied using a moving average technique to smooth short-term sensor fluctuations, while outlier removal was performed using z-score thresholding to eliminate extreme values caused by temporary sensor drift [13]. All measurements were then synchronized into a unified timestamp format. Following preprocessing, feature engineering was conducted to derive secondary indicators relevant to environmental stability assessment. These indicators included the rate of change for pH, DO, and temperature, as well as a daily stability index based on variance analysis. Anomaly markers were also generated to identify sudden parameter deviations that may indicate unfavorable environmental conditions.

The processed dataset was aggregated into hourly averaged time-series values to facilitate trend analysis and visualization. Representative time-series samples are presented in Table 3, while detailed hourly averaged sensor data are provided in Appendix A. These engineered features were subsequently integrated with consumer behavior data to analyze correlations between water quality stability and market-driven preferences.

**Consumer Behavior Data Acquisition**

Consumer behavior data were collected through an online questionnaire distributed to 50 koi fish hobbyists and buyers located in East Java, Indonesia. The questionnaire was designed to capture key behavioral and purchasing characteristics relevant to koi fish cultivation and market preferences. The survey instrument combined structured multiple-choice questions and Likert-scale ratings to obtain consistent and quantifiable responses.

The questionnaire addressed three main dimensions of consumer behavior. The first dimension focused on purchase decision factors, including preferences related to color and pattern quality, body size considerations, price sensitivity, and perceived reputation of koi farms. The second dimension examined maintenance-related behavior, such as the frequency of water replacement, feeding practices, and the willingness to invest in supporting equipment, including aeration and filtration systems. The third dimension explored brand loyalty and spending tendencies by assessing preferred suppliers, interest in equipment upgrades, and approximate monthly budget allocation for koi-related expenditures.


Figure 3. Consumer Decision Making

Figure 3 the conceptual structure of the consumer decision-making process used in this study, highlighting the relationships between aesthetic preferences, maintenance considerations, and purchasing behavior. Prior to analysis, the collected dataset underwent preprocessing steps, including categorical variable encoding, normalization of numerical attributes, and the removal of incomplete or inconsistent responses to ensure data quality and analytical reliability.

**Integrated Data Analysis**

An integrated analytics pipeline was implemented using Python to jointly analyze environmental IoT data and consumer behavior data. The analytical process was designed to identify relationships between water quality stability and consumer perceptions relevant to sustainable koi fish cultivation. The analysis combined descriptive statistics, correlation analysis, and clustering techniques to generate actionable insights for cultivation management and market alignment.

Statistical correlation analysis was first conducted to examine associations between water quality stability indicators, particularly pH variability and dissolved oxygen (DO) fluctuations, and selected consumer behavior variables, including maintenance awareness and spending tendencies. Both Pearson and Spearman correlation coefficients were applied to accommodate linear and monotonic relationships. This analysis aimed to assess whether more stable environmental conditions were associated with higher perceived product value and stronger consumer preferences.

To further characterize consumer diversity, K-Means clustering was employed to segment respondents into distinct behavioral groups based on survey responses. The optimal number of clusters was determined using the elbow method and validated through silhouette coefficient analysis. The resulting clusters were interpreted as quality-focused, budget-conscious, and maintenance-oriented consumer segments, reflecting differences in aesthetic preferences, price sensitivity, and willingness to engage in maintenance-related activities.

Finally, an integrated cross-analysis was performed to link the environmental IoT data with consumer segmentation outcomes. This stage involved comparing water quality stability patterns with the preferences and expectations of each consumer cluster, as well as examining representative environmental conditions in relation to perceived fish value. The combined analysis enabled the identification of decision-support insights that connect cultivation performance indicators with potential market strategies, supporting more informed and sustainable koi farming practices.

## RESULT AND DISCUSSION

The integrated dataset consists of two primary components: (1) IoT-based water quality measurements collected over a 30-hour observation window, then detailed time-series data are provided in Appendix A; (2) consumer behavior survey responses from koi enthusiasts. Both datasets were analyzed to evaluate environmental stability in koi aquaculture and its alignment with consumer-driven preferences.

### IoT Sensor Data Analysis

The IoT-based monitoring system continuously recorded water quality parameters over a 30-hour observation period, enabling detailed assessment of environmental stability in koi fish cultivation. The monitored parameters included pH, dissolved oxygen (DO), temperature, and turbidity, all of which are critical indicators of koi health and growth performance. Analysis of the time-series data reveals a cyclical fluctuation pattern in both pH and DO levels throughout the monitoring period. During the early phase of observation, pH values exhibited a gradual decline, followed by a recovery phase toward the end of the monitoring period. A comparable trend was observed in DO concentrations, which decreased moderately before stabilizing at higher levels in the later observation hours. These fluctuation patterns reflect typical biological processes in closed aquatic systems, such as respiration activity, organic matter decomposition, and microbial dynamics.

To provide a concise quantitative overview of the observed water quality conditions, Table 1 summarizes the minimum, maximum, and mean values of each monitored parameter during the 30-hour observation period. As shown in Table 1, pH values remained within a neutral to slightly acidic range, while DO concentrations consistently exceeded 6.0 mg/L. Temperature and turbidity also showed limited variation, suggesting stable thermal conditions and acceptable water clarity throughout the observation.

Overall, all measured parameters remained within acceptable thresholds for koi fish cultivation. Dissolved oxygen levels stayed above the minimum requirement for optimal koi well-being, while pH stability supported healthy metabolic activity and coloration development. These findings demonstrate that the proposed IoT monitoring system effectively captures subtle environmental fluctuations that may not be detected through periodic manual measurements. Continuous monitoring thus enables early detection of potential deviations and supports timely micro-adjustments, contributing to sustainable and data-driven koi aquaculture management.

Table 1. Summary Statistics of IoT Water Quality Measurements

| Parameter | Minimum | Maximum | Mean |
|---|---|---|---|
| pH | 6.66 | 7.20 | 6.95 |
| DO (mg/L) | 6.0 | 7.1 | 6.6 |
| Temparature (°C) | 26.6 | 27.6 | 27.1 |
| Turbidity (NTU) | 12 | 18 | 15 |

These fluctuation patterns are consistent with recent IoT-based aquaculture studies, which report that pH and DO commonly exhibit cyclical variations within enclosed water systems due to respiration, feeding metabolism, and microbial decomposition [1], [10]. Continuous monitoring enables early detection of such micro-variations, contributing to sustainable and data-driven koi aquaculture management. Similar findings have also been reported in sustainable aquaculture research, emphasizing that environmental stability significantly supports fish coloration, immune performance, and long-term survival outcomes [14]. Detailed time-series measurements supporting these observed trends are provided in Appendix A.

## Consumer Behavior Survey Analysis

The consumer behavior survey reveals distinct preference distributions across key behavioral factors. Color preference, particularly for bright red and white koi varieties, shows the highest influence, with 65% of respondents rating it as highly important. Maintenance awareness was also significant, with 58% exhibiting high concern for water quality and routine care.

Table 2. Consumer Behavior Survey Results

| Behavioral Aspect | High Preference (%) | Medium (%) | Low (%) |
|---|---|---|---|
| Color Preference (Bright Red/White) | 65 | 25 | 10 |
| Purchase Frequency (>3x/year) | 42 | 38 | 20 |
| Maintenance Awareness | 58 | 33 | 9 |
| Price Sensitivity | 40 | 37 | 23 |

In contrast, purchase frequency and price sensitivity demonstrated more balanced distributions across high, medium, and low categories, suggesting that buying behavior is more varied among hobbyists. For example, 42% reported purchasing koi more than three times per year, while 37% indicated medium price sensitivity, reflecting a mixed market segment consisting of premium buyers and budget-oriented hobbyists [15] [16]. These preference distributions are aligned with recent consumer analytics findings, where visual attributes such as coloration intensity and pattern clarity consistently rank as strong purchase motivators in ornamental and aquatic livestock markets [5], [6].

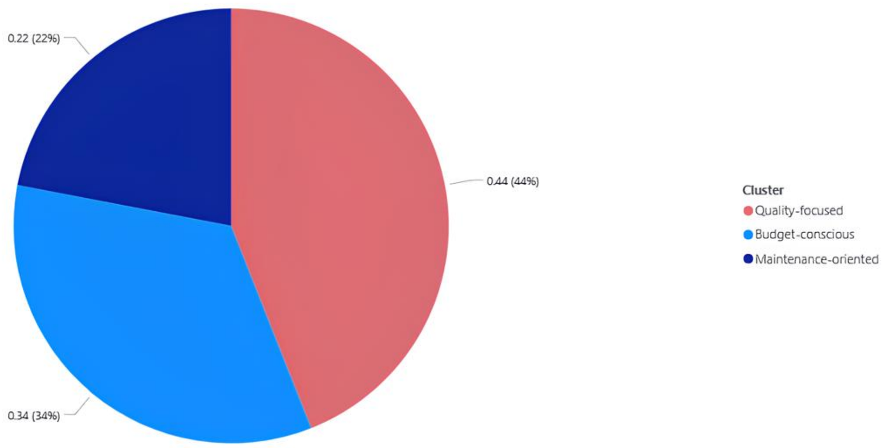


Figure 4. Consumer Behavior Segmentation in Koi Fish Market

Behavioral studies in 2024 also confirm that maintenance awareness and long-term care capacity significantly shape purchasing decisions, especially among hobbyists who prioritize fish health stability over price sensitivity [17]. This strengthens the evidence that purchase behavior in ornamental aquaculture is driven by a combination of aesthetic perception, maintenance readiness, and willingness to invest in long-term care. These findings enabled the formation of three dominant consumer segments:

1. Quality-Focused: Prioritize coloration, body shape, and health stability.
2. Budget-Conscious: Sensitive to price fluctuations and prefer affordable maintenance
3. Maintenance-Oriented: Highly aware of water quality and husbandry routines

## Integrated Interpretation: Linking IoT Data to Consumer Insights

When IoT data trends are compared with consumer segmentation, a coherent relationship emerges. The stability of pH and dissolved oxygen in the IoT system directly supports the expectations of the Quality-Focused and Maintenance-Oriented consumer segments [18]. These groups collectively represent a large portion of surveyed consumers and place high emphasis on fish health, appearance, and long-term survival factors that are highly dependent on water quality [17] [12].

Furthermore, the environmental fluctuations captured by the IoT system highlight the necessity of real-time monitoring, particularly for maintenance-oriented consumers who frequently adjust water conditions to maintain optimal fish health [13]. For Budget-Conscious buyers, the observed data support the argument that automated IoT-based monitoring systems may reduce long-term operational costs by preventing mortality events and minimizing water deterioration. This demonstrates that IoT-enabled monitoring not only enhances biological outcomes but also contributes to cost efficiency in koi fish cultivation.

The relationship between environmental stability and consumer perception in this study aligns with recent behavioral research, which indicates that digital media cues and environmental information strongly influence how consumers evaluate product quality and make purchasing decisions [19]. In addition, the alignment between environmental stability and consumer preferences is supported by behavioral analytics studies showing that buyers increasingly associate water quality consistency with perceived fish value, coloration strength, and longevity expectations [7], [20]. Furthermore, research in 2024–2025 demonstrates that integrating environmental data with consumer segmentation helps predict market responses more accurately, enabling producers to match cultivation strategies with evolving customer expectations [18], to illustrate representative water quality conditions during the monitoring period, Table 3 presents selected hourly averaged sensor readings at different observation intervals.

Table 3. Representative Time-Series IoT Sensor Measurements (Hourly Average)

| Time (h) | pH | DO (mg/L) | Temperature (°C) | Turbidity (NTU) |
|---|---|---|---|---|
| 0 | 7.2 | 6.8 | 27.5 | 12 |
| 6 | 6.9 | 6.5 | 27.0 | 14 |
| 9 | 6.8 | 6.3 | 26.8 | 16 |
| 12 | 6.7 | 6.1 | 26.6 | 18 |

To further illustrate this relationship, Table 3 presents representative hourly averaged sensor readings at selected observation intervals, demonstrating stable water quality conditions throughout the monitoring period. While Table 3 highlights representative time snapshots, Figure 5 visualizes the overall time-series trends of pH and dissolved oxygen, and Appendix A provides detailed hourly averaged sensor data supporting the integrated analysis. Together, these results indicate that combining IoT-derived environmental data with consumer behavior analytics enables koi farmers to make operational decisions that align biological requirements with market expectations, thereby supporting data-driven and sustainable koi aquaculture practices.

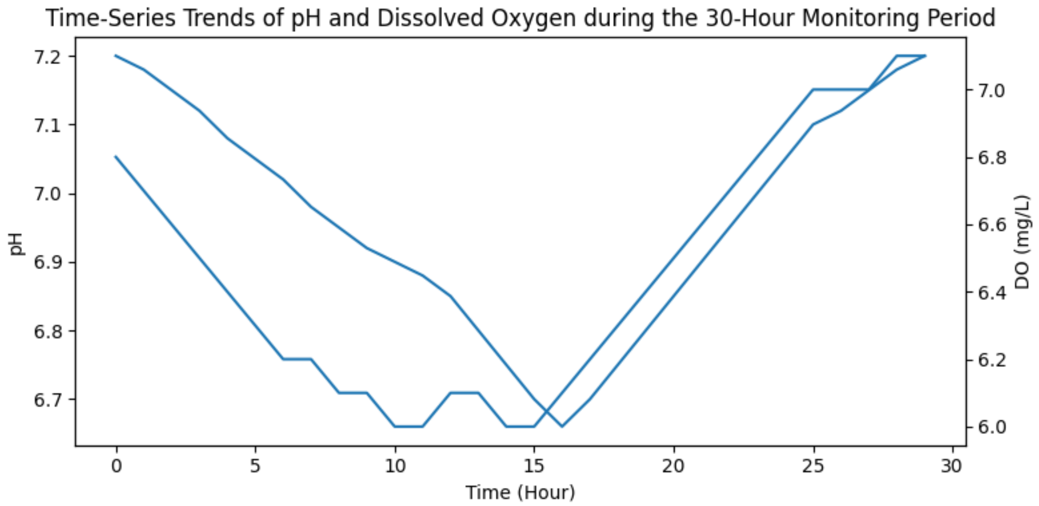


Figure 5. Time-Series Trends of pH and Dissolved Oxygen during the 30-Hour Monitoring Period

## CONCLUSION

This study demonstrates that integrating IoT-based water quality monitoring with consumer behavior analytics provides a practical and data-driven approach to supporting sustainable koi fish cultivation. The implemented IoT system successfully recorded time-series variations in key water quality parameters, particularly pH and dissolved oxygen, over a 30-hour observation period. The observed fluctuations remained within acceptable physiological ranges for koi fish, indicating that continuous monitoring can effectively support stable cultivation conditions and timely decision-making compared to intermittent manual measurements.

The consumer behavior analysis identified three dominant market segments—Quality-Focused, Budget-Conscious, and Maintenance-Oriented—each characterized by distinct preferences related to fish appearance, maintenance effort, and purchasing considerations. When linked with IoT-derived water quality stability patterns, the results indicate that consistent environmental conditions are closely aligned with the expectations of Quality-Focused and Maintenance-Oriented consumers. In addition, the adoption of automated IoT-based monitoring systems demonstrates potential operational advantages that are relevant to Budget-Conscious buyers by supporting more efficient resource management.

Overall, the proposed integrated framework highlights how combining environmental sensing data with consumer behavior insights can enhance operational awareness, improve market alignment, and contribute to sustainable aquaculture practices. Future work may expand this approach through longer monitoring periods, larger-scale deployments, predictive analytics, and the integration of automated control mechanisms to further strengthen smart aquaculture decision-support systems.

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# APPENDIX A

## Sample Time-Series IoT Sensor Data

This appendix presents representative time-series data derived from continuous IoT-based water quality monitoring conducted over a 30-hour observation period. The IoT system recorded sensor readings at 30-second intervals; however, due to space limitations, this appendix reports hourly averaged values to demonstrate data consistency and trend behavior.

Table A.1. Hourly Averaged IoT Sensor Measurements

| Time (Hour) | pH | DO (mg/L) | Temperature (°C) | Turbidity (NTU) |
|---|---|---|---|---|
| 0 | 7.20 | 6.8 | 27.5 | 12 |
| 1 | 7.18 | 6.7 | 27.4 | 12 |
| 2 | 7.15 | 6.6 | 27.3 | 13 |
| 3 | 7.12 | 6.5 | 27.2 | 13 |
| 4 | 7.08 | 6.4 | 27.1 | 14 |
| 5 | 7.05 | 6.3 | 27.0 | 14 |
| 6 | 7.02 | 6.2 | 26.9 | 15 |
| 7 | 6.98 | 6.2 | 26.9 | 15 |
| 8 | 6.95 | 6.1 | 26.8 | 15 |
| 9 | 6.92 | 6.1 | 26.8 | 16 |
| 10 | 6.90 | 6.0 | 26.7 | 16 |
| 11 | 6.88 | 6.0 | 26.7 | 17 |
| 12 | 6.85 | 6.1 | 26.6 | 17 |
| 13 | 6.80 | 6.1 | 26.6 | 18 |
| 14 | 6.75 | 6.0 | 26.6 | 18 |
| 15 | 6.70 | 6.0 | 26.6 | 18 |
| 16 | 6.66 | 6.1 | 26.7 | 17 |
| 17 | 6.70 | 6.2 | 26.8 | 17 |
| 18 | 6.75 | 6.3 | 26.9 | 16 |
| 19 | 6.80 | 6.4 | 27.0 | 16 |
| 20 | 6.85 | 6.5 | 27.1 | 15 |
| 21 | 6.90 | 6.6 | 27.2 | 15 |
| 22 | 6.95 | 6.7 | 27.3 | 14 |
| 23 | 7.00 | 6.8 | 27.4 | 14 |
| 24 | 7.05 | 6.9 | 27.5 | 13 |
| 25 | 7.10 | 7.0 | 27.6 | 13 |
| 26 | 7.12 | 7.0 | 27.6 | 13 |
| 27 | 7.15 | 7.0 | 27.6 | 12 |
| 28 | 7.18 | 7.1 | 27.6 | 12 |
| 29 | 7.20 | 7.1 | 27.5 | 12 |

*Appendix Notes*

- All values represent hourly averaged measurements derived from raw sensor readings recorded every 30 seconds.
- The reported data demonstrate cyclical trends and stability patterns consistent with controlled koi aquaculture environments.
- Complete raw datasets are archived and available upon request.