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An Interactive Augmented Reality and Digital Twin Framework for IoT-Based Aquaponics in Urban Farming

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ABSTRACT

Urban farming, specifically aquaponics, offers a sustainable approach to food production; however, novice practitioners often struggle due to the complexity of the system and a reliance on stable internet connectivity for real-time monitoring. This paper proposes an interactive Augmented Reality (AR) and Digital Twin (DT) framework for IoT-based aquaponics to address these limitations. Developed through a rigorous five-phase research methodology, the system integrates a resilient WebSocket communication architecture with edge-level data buffering, successfully recovering 92.38% of sensor records during simulated network outages. To sustain continuous environmental visualisation during hardware or network failures, a lightweight slope-only linear regression fallback mechanism was implemented, achieving high predictive accuracy ($R^2 > 0.9$) for dynamic parameters like temperature and humidity. Furthermore, to accommodate non-technical urbanites (aged 18 to 35), the mobile AR interface incorporates a rule-based mistouch detection algorithm using spatial and temporal thresholds, successfully intercepting 37.25% of interactions as accidental inputs to prevent physical actuation errors. A User Acceptance Test (UAT) with 20 participants yielded a System Usability Scale (SUS) score of 56.63, reflecting the initial cognitive load of spatial AR navigation, yet recorded a high overall user satisfaction rate of 85%. This paper contributes a resilient, fault-tolerant, and user-centric management solution that advances smart agriculture for urban farming initiatives.

Keywords: Aquaponics, augmented reality, digital twin, internet of things, smart agriculture, urban farming, user acceptance testing

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INTRODUCTION

The global challenge of sustainability and efficient food production has been exacerbated by the rapid increase in urbanisation, climate change, and food security issues. Urban farming has been established to solve problems with food access through localised food production, while also decreasing the carbon footprint of food production compared to traditional farms. Urban farming has taken off in Malaysia, with the number of urban farms jumping from 735 in 2019 to over 17,000 in 2020, which indicates an increased interest in sustainable agriculture and food resilience for the public through new initiatives for urban farms.

Figure 1 illustrates that the most common forms of urban farming are aquaponics, which is a sustainable form of agriculture that integrates aquaculture and hydroponics into a symbiotic environment. The integration of aquaculture and hydroponic farming allows the simultaneous farming of fish and land-based plants for food. (Ibrahim et al., 2023). With the incorporation of aquaponics into urban sustainable agriculture, resource use efficiency is maximised and less environmental impact compared to traditional agriculture. However, small-scale or start-up aquaponic practitioners tend to struggle with technical skills, real-time monitoring opportunities, and the end-user cognitive load from relying on intuition and decision-making processes (Yanes et al., 2020).

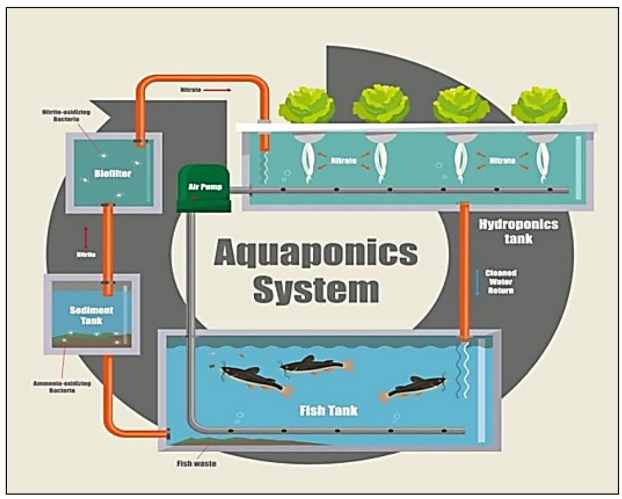

Figure 1. Illustration of an aquaponics system (Bambhaniya et al., 2023)

To address these operational difficulties, recent studies have explored the integration of the IoT, AR, and DT technologies. IoT systems are traditionally employed to provide real-time monitoring of essential parameters such as pH, temperature, and nutrient levels (Mahmoud et al., 2023; Ntulo et al., 2021). AR facilitates spatial interaction by overlaying this real-time data onto the physical environment (Wong et al., 2024), while DT models provide a virtual replica for system simulation and analysis (Verdouw et al., 2021). However, while these technologies represent significant advancements, a critical analysis of the current literature reveals that their mainstream integration into aquaponics remains insufficient. Most existing approaches treat these technologies as isolated tools rather than a cohesive ecosystem, leading to unresolved operational vulnerabilities. Specifically, current IoT architectures in smart agriculture assume ideal, stable internet connectivity; consequently, they suffer from severe data loss and delayed system feedback during the intermittent network outages common in urban and remote farming environments (Channa et al., 2024; Taha et al., 2022).

Furthermore, existing AR interfaces designed for aquaponics often introduce new usability barriers for non-technical users. Because mobile AR environments lack tactile feedback, users frequently execute accidental commands, commonly referred to as "mistouches", which can unintentionally trigger physical system actuators (Yamanaka & Usuba, 2021; Zamnuri et al., 2024). Current literature lacks the implementation of rigorous HCI safeguards, such as spatial and temporal filtering, to prevent these critical interaction errors (Cockburn et al., 2019; Subramanian et al., 2021). Additionally, current DT implementations typically rely on continuous cloud synchronisation, meaning the virtual visualisation freezes or fails when physical sensors or network connections are interrupted. The absence of lightweight predictive fallback mechanisms to estimate environmental conditions during these outages disrupts system continuity and heavily erodes user trust (Lin et al., 2022; Otieno, 2023).

To address these specific research gaps, this study proposes a comprehensive DTIAR framework that tightly integrates IoT sensors, real-time DT synchronisation, and error-resistant AR interfaces into aquaponic systems. Unlike previous studies that merely combine existing technologies, this research introduces three novel advancements to ensure structural resilience and user accessibility. First, it implements a WebSocket-based communication architecture equipped with edge-level data buffering to mitigate data loss during network instability. Second, it embeds a rule-based mistouch detection algorithm within the AR interface to safely filter accidental inputs from novice users. Finally, it incorporates a slope-only simple linear regression predictive fallback mechanism to sustain continuous environmental visualisation even during complete sensor or network failures. By critically addressing the deficiencies of current smart farming systems, this paper provides a highly resilient, scalable, and user-centric DTIAR model suitable for learning institutions, urban farming programs, and community-driven sustainability initiatives.

Problem Statement

Global food systems are increasingly stressed by rapid population growth, climate change, and the scarcity of natural resources. Therefore, sustainable and novel agricultural methods, such as aquaponics, are essential (Food and Agriculture Organisation of the United Nations, 2022). Aquaponics represents a highly productive alternative for food production, combining aquaculture and hydroponics in a symbiotic relationship. Nonetheless, the widespread application and potential success of aquaponics systems are currently limited by several critical technological barriers.

First, many modern aquaponics systems are unable to provide reliable real-time monitoring and control due to unstable internet connectivity, resulting in delayed system feedback and severe data loss. Current systems are often not designed to function optimally with real-time data under fluctuating network conditions (Channa et al., 2024; Taha et al., 2022). Consequently, it is difficult for users to make quick responses regarding water quality, nutrient flows, and temperature, which hampers the system's biological stability (Chandramenon et al., 2024; Kok et al., 2024; Ntulo et al., 2021). Crucially, there is a lack of robust communication architectures that utilise local data buffering and deferred synchronisation to prevent data loss during these internet connectivity dropouts.

Second, existing AR aquaponics interfaces are highly prone to user interaction errors, which hinder effective system operation by non-technical users. Poorly designed mobile interfaces frequently lead to interaction errors, specifically accidental inputs or "mistouches". These interaction errors minimise usability, trigger unintended physical actuations, and deter user engagement, especially in educational or small-scale urban farming situations (Karimanzira & Rauschenbach, 2019; Mohamad et al., 2024; Zamnuri et al., 2024).

Third, many existing aquaponics monitoring systems are unable to maintain continuous environmental monitoring during internet outages or physical sensor interruptions. This disruption results in missing sensor data, halting system visualisation, which breaks operational continuity and erodes user trust (Eneh et al., 2023; Garzón et al., 2022; Sundararajan et al., 2025; Zamnuri et al., 2024). Specifically, these systems lack a lightweight predictive fallback mechanism capable of estimating and sustaining continuous data visualisation when physical sensors or networks temporarily fail.

To overcome these barriers, a responsive and robust framework is required. This framework must incorporate a live, low-latency communication layer using WebSocket with local buffering, an AR user interface equipped with a mistouch-prevention strategy, and a predictive fallback mechanism to ensure continuity of the user experience even during disturbances to the communication channel.

Aim of the Study

The overarching aim of this study is to improve the usability and resilience of smart aquaponic systems for non-technical users through the integration of IoT, DT and AR technologies. To realise this goal, the research pursues three specific, measurable objectives. First, it aims to enhance the communication architecture by integrating a resilient, WebSocket-based approach equipped with local data buffering and deferred synchronisation to significantly reduce data loss during intermittent network connectivity. Second, it seeks to improve the operational reliability of the AR interface by formulating a rule-based mistouch detection algorithm that utilises predefined spatial and temporal thresholds to accurately distinguish intentional user commands from accidental inputs. Finally, the study aims to ensure the continuity of environmental data visualisation during hardware or network failures by implementing a lightweight, slope-only linear regression model ($\hat{y}_{n+1} = y_n + \beta_1$) as a predictive fallback mechanism within the mobile application.

LITERATURE REVIEW

The incorporation of digital technologies into aquaponics systems has increasingly focused on the IoT, AR, and DT to automate environmental controls and enhance user engagement. The deployment of IoT technologies has successfully transitioned aquaponics from passive observation to active, automated regulation, with recent studies demonstrating accessible microcontroller-based monitoring (Ntulo et al., 2021) and modular cloud-based agro-toolboxes (Pechlivani et al., 2023). However, a critical synthesis of these systems reveals a shared vulnerability: a heavy reliance on continuous, ideal network conditions (Wan et al., 2022). In practical agricultural deployments, unstable connectivity frequently leads to delayed system feedback and permanent data loss, detrimentally affecting ecosystem health (Channa et al., 2024; Taha et al., 2022). Existing literature predominantly lacks communication architectures explicitly designed to handle intermittent network outages through edge-level local data buffering and deferred synchronisation (Alselek et al., 2022).

To improve user engagement and data accessibility, AR is increasingly implemented to spatially visualise environmental metrics. Recent applications have successfully utilised mobile AR to overlay digital plant information onto physical crops, significantly increasing knowledge retention for novice users (Garzón et al., 2022; Yi Chien & Norasri Ismail, 2022). Despite this visual potential, current AR frameworks present a critical HCI limitation: they rely on static tap interfaces without safeguards against interaction errors. When non-technical users interact with floating 3D elements on mobile screens, the lack of tactile feedback frequently leads to accidental activations, or "mistouches" (Yamanaka & Usuba, 2021; Zamnuri et al., 2024). While HCI literature establishes that embedding strict spatial constraints and temporal thresholds can significantly improve reliability (Cockburn et al., 2019; Subramanian et al., 2021).These heuristic rules have not been sufficiently integrated into live agricultural AR interfaces to prevent the unintended triggering of physical actuators.

Furthermore, DT technology is increasingly utilised to develop virtual replicas of physical systems for continuous monitoring (Pylianidis et al., 2021). Advanced implementations have employed deep learning approaches, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, to forecast complex environmental dependencies (Sundararajan et al., 2025). However, these sophisticated models demand extensive computational power and large training datasets, creating a high barrier to entry for small-scale urban farmers. More critically, most existing DT assume perfect hardware reliability; when physical sensors fail or disconnect, the virtual visualisation freezes or fails. There is a significant gap in the literature regarding the use of lightweight, computationally efficient models such as simple linear regression, which has shown high accuracy in aquaculture forecasting (Eneh et al., 2023), to act as immediate predictive fallback mechanisms capable of sustaining visual continuity during these outages.

In summary, a comparative analysis underscores a pervasive fragmentation within current smart agriculture literature, where research typically prioritises isolated technological optimisation over holistic, resilient integration. Table 1 provides a systematic comparative evaluation of key recent studies, highlighting the specific functional limitations of existing frameworks compared to the proposed system. While existing studies have pioneered AR educational tools (Garzón et al., 2022) and advanced predictive models (Sundararajan et al., 2025). They remain highly vulnerable to network instability and user interaction errors in real-world deployments. The proposed framework fundamentally differs from previous studies by bridging these silos: it integrates WebSocket-based edge buffering to ensure data integrity during network drops, embeds rule-based mistouch detection directly into the AR spatial interface to safeguard against user errors, and deploys a lightweight predictive fallback mechanism to maintain operational continuity. This integrated approach ensures a fault-tolerant, user-centric system that overcomes the distinct technical limitations of preceding standalone implementations.

Table 1
Summary of key studies on IoT, AR, and DT applications in aquaponic systems

Study (Year)	Technologies	Key Strengths	Identified Limitations
Ntulo et al., 2021	IoT, Microcontrollers	Accessible, low-cost real-time monitoring.	Assumes stable networks; lacks local data buffering, leading to data loss during outages.
Verdouw et al., 2021	DT	Real-world validation in commercial agriculture.	High implementation complexity; relies on continuous cloud synchronisation without fallback mechanisms.
Garzón et al., 2022	Augmented Reality	High user engagement via spatial visualisation.	Lacks HCI safeguards (spatial/temporal thresholds) to prevent accidental mistouches.
Sundararajan et al., 2025	IoT, Deep Learning	High predictive accuracy for environmental conditions.	Computationally intensive; lacks lightweight fallback options for continuous visualisation during sensor failures.
Proposed DTIAR Framework (2026)	IoT, AR, DT	Resilient, user-centric, and continuous system monitoring.	Addresses existing gaps by integrating WebSocket edge-buffering, rule-based AR mistouch detection, and an SLR predictive fallback mechanism.

METHODOLOGY

To ensure the proposed DTIAR framework satisfies both rigorous technical standards and end-user requirements, this study employs an iterative, design-based research methodology. Moving beyond a standard software development workflow, the research design is systematically structured into five sequential phases: Formulation and Planning, System Development, Evaluation and Refinement, Final Validation and Analysis, and Finalisation and Documentation.

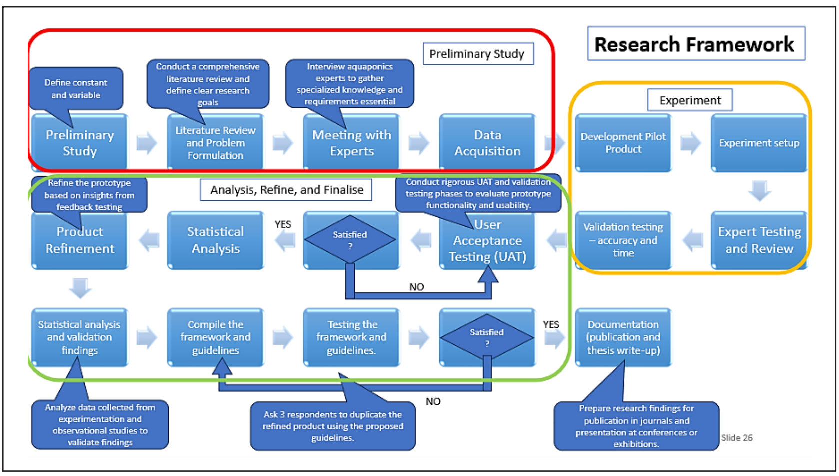

Figure 2. Research framework diagram

As illustrated in Figure 2, this research framework clearly maps the inputs, decision criteria, and outputs across the study. During the Formulation phase, preliminary expert sub-studies served as primary inputs, where consultations with an architectural design expert and an aquaculture specialist established critical biological safety thresholds (such as maintaining water pH between 6.5 and 7.5) and validated the physical system layout. Following the integration of IoT hardware and the AR interfaces during System Development, the Evaluation and Refinement phase utilised an initial pilot study comprising 50 participants to assess early-stage AR interaction mechanics. The output of this pilot study directly influenced the system's decision criteria, leading to critical adjustments in the interactive bounding boxes to reduce user cognitive load before moving to final testing.

To provide a comprehensive evaluation of the system's technical performance and address the relationships among IoT, DT, and AR components, the Final Validation phase employed explicit, objective evaluation metrics across three core variables. First, the resilience of the IoT communication architecture was evaluated by measuring data recovery and completion rates during simulated intermittent network outages to validate the efficacy of the local edge-buffering mechanism. Second, the reliability of the AR interface was quantified by logging touch interactions and calculating the mistouch classification rate. This classification acted as a strict decision criterion, governed by specific heuristic thresholds: a spatial Movement Distance Threshold (invalidating touches exceeding 25 pixels) and a temporal Touch Duration Threshold (flagging contacts lasting longer than 400 milliseconds as unintentional) (Cockburn et al., 2019; Yamanaka & Usuba, 2021). Third, the accuracy of the DT's predictive fallback mechanism was rigorously evaluated using standard statistical error metrics, specifically MSE, RMSE, MAE, and R^2 to compare the algorithm's forecasted values against actual sensor data recovered post-reconnection (Chicco et al., 2021).

To measure user perceptions regarding usability and satisfaction, a formal User Acceptance Test (UAT) was conducted during the Final Validation phase. The study utilised a purposive sampling strategy, selecting 20 participants. The inclusion criteria explicitly targeted young adult urbanites (aged 18 to 35) who possessed baseline digital and smartphone literacy but lacked prior technical training or expertise in aquaponics or smart farming systems. The selection of a 20-participant sample size for the final UAT is scientifically justified by established Human-Computer Interaction (HCI) research, which demonstrates that a sample of 20 users provides a 95% probability of uncovering major system usability issues (Faulkner, 2003). Data collection for the UAT was conducted using a structured, digital questionnaire comprising demographic profiling, task-based ratings, and the standardised 10-item SUS (Brooke, 2020). Participants rated items on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). To ensure the statistical reliability and internal consistency of the survey instrument, Cronbach's alpha (α) was calculated for the collected responses. Finally, because this phase of the study involved human participants, strict ethical considerations were observed throughout the evaluation process. Informed consent was formally secured from all participants before they engaged with the system, and all collected demographic feedback and interaction data were fully anonymised to protect participant confidentiality and ensure data privacy.

System Interface and Functional Design

The mobile application serves as the User Layer of the DTIAR framework, developed utilising the Unity 3D engine and ARCore to seamlessly bridge the physical and digital domains. As illustrated in the application storyboard in Figure 3, the user experience is structured around three primary functional modules designed to support non-technical practitioners: the Status Page, the AR Page, and the Settings Page. The Status Page functions as the central dashboard, providing real-time data visualisation of critical environmental parameters such as water temperature, pH, humidity, and light intensity through numeric values, colour-coded alerts, and graphical gauges. The AR Page immerses the user by superimposing live telemetry readings and 3D models directly onto the corresponding physical aquaponics infrastructure via markerless tracking, facilitating intuitive spatial learning. Finally, the Settings Page allows users to configure application preferences, including theme customisation, font sizes, and specific notification thresholds.

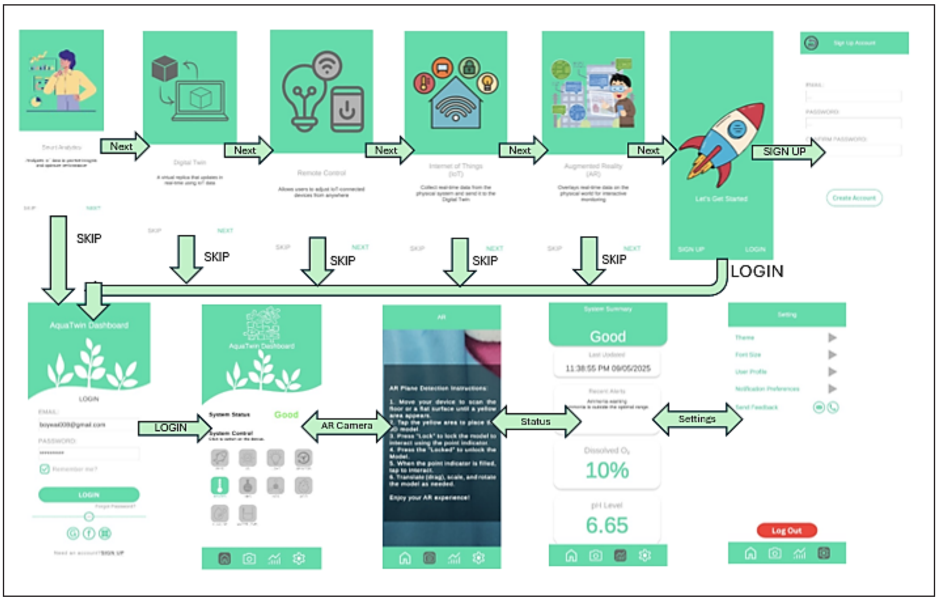

Figure 3. Storyboard of the application

To ensure the application satisfies recognised usability principles, particularly for novice users operating in complex spatial environments, the interface design requirements were strictly derived from established Human-Computer Interaction (HCI) heuristics. Mobile AR environments frequently suffer from the "fat finger problem," where the inherent instability of holding a mobile device and the lack of tactile haptic feedback led to high rates of accidental actuations. To mitigate this, the AR interface evaluates every user interaction against a newly integrated, rule-based mistouch detection algorithm configured with strict quantitative design thresholds. Specifically, the system applies a Movement Distance Threshold that invalidates any touch involving more than 25 pixels of movement, successfully differentiating a deliberate tap from an unintentional drag (Parhi et al., 2006).

Additionally, the interface evaluates inputs against a Touch Duration Threshold, categorising any contact lasting longer than 0.4 seconds (400 milliseconds) as an accidental resting touch to ensure only rapid, decisive inputs are processed as commands (Cockburn et al., 2019). Finally, the design enforces a precise Button Target Zone, requiring user interactions to land within the central 30–70% of the interactive button area to be registered as valid. By systematically evaluating user inputs against these recognised HCI principles, the interface safely filters out accidental mistouches. This design significantly reduces the cognitive load on novice users and serves as a critical operational safeguard, preventing unintentional triggers of the physical aquaponics actuators during AR navigation.

System Architecture and Connectivity

The DTIAR system connects IoT, DT, and AR technology as a single smart aquaponics management platform accessible via a mobile application. To ensure true DT synchronisation extending beyond mere 3D visualisation by maintaining continuous, bidirectional correspondence between the physical and virtual environments, the system architecture is engineered into a decentralised five-layer framework: the Edge/Physical Layer, Network Layer, Cloud Layer, Intelligence Layer, and User Layer. As illustrated in Figure 4, the architecture governs the precise flow of time-series data and control signals across the ecosystem.

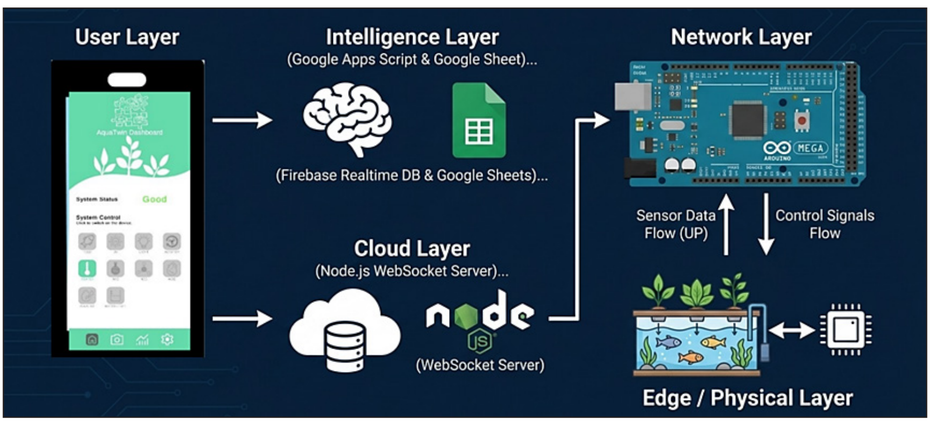

Figure 4. Full system architecture

The foundation of the architecture resides in the Edge/Physical Layer, which comprises the physical aquaponics infrastructure (fish tanks, plant beds, and LED grow lights) alongside the environmental sensor suite and physical actuators. Data acquisition and hardware control are managed within the Network Layer by an Arduino MEGA R3 + Wi-Fi (ATmega2560 + ESP8266) microcontroller. The ATmega2560 handles high-frequency analogue and digital reads from sensors, including the analogue pH meter, TDS/EC sensor, waterproof DS18B20 digital temperature probe, DHT22 air temperature/humidity sensor, HC-SR04 ultrasonic water level sensor, and GY-30 light intensity sensor, while the onboard ESP8266 manages wireless communication. To protect against data loss during network instability, the microcontroller maintains a local edge-buffering memory queue; when internet connectivity is interrupted, telemetry is stored locally and transmitted via deferred batch synchronisation upon reconnection, ensuring zero historical data loss.

The Cloud Layer serves as the central communication and storage broker, utilising a Node.js WebSocket server hosted on Render.com paired with a Firebase Realtime Database. The technical selection of a WebSocket protocol over traditional HTTP polling is justified by the necessity for persistent, full-duplex communication, which successfully reduces average communication latency to under 200 milliseconds. Sensor data flows upward from the microcontroller as formatted JSON payloads, updating Firebase in real-time and broadcasting live updates to all connected Unity clients. Conversely, user control commands flow downward from the mobile app through the WebSocket to Firebase, instantly triggering physical relays (such as acid/alkaline dosing pumps or aerators) on the hardware.

Operating concurrently with the cloud backend is the Intelligence Layer, which drives the DT's predictive fallback mechanism via Google Apps Script. If the system experiences a network dropout exceeding 30 seconds, the intelligence engine automatically triggers a lightweight, slope-only simple linear regression model $(\hat{y}_{n+1} = y_n + \beta_1)$. By extrapolating from recent historical observation windows, the model calculates and injects estimated sensor values into the database. As shown in Figure 5, these forecasted values maintain visual and data continuity within the AR interface, preventing the visualisation gaps typically associated with connectivity failures. Upon reconnection, an automated recovery protocol overwrites the synthetic estimates with actual physical telemetry, ensuring complete data integrity.

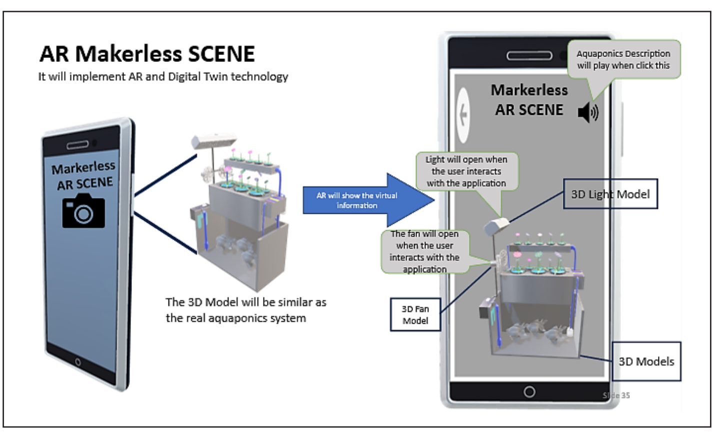

Figure 5. AR scene of the application

The successful integration of IoT sensors, real-time DT synchronisation, and augmented reality technologies effectively addresses the operational limitations of distance, latency, and data complexity highlighted in the research problem statement. By combining the seamless real-time data collection of the DT with lightweight predictive analytics, the system maintains consistent oversight of critical water quality parameters, nutrient levels, and temperatures without requiring continuous manual intervention. Furthermore, the AR interface successfully democratises system interaction, lowering the technical barrier to entry and enabling users across the technical ability spectrum to engage in efficient, immersive smart agriculture management.

RESULT AND DISCUSSIONS

Technical Evaluation of System Objectives

To validate the technical effectiveness and operational resilience of the proposed framework, the system was evaluated across three core objectives: communication resilience, AR interaction reliability, and predictive fallback accuracy.

First, communication resilience was objectively assessed to quantify the system's ability to prevent data loss during network interruptions. Under stable conditions, the WebSocket architecture successfully maintained a low-latency bidirectional data stream with an average upload interval of 5.8 seconds and a standard deviation of only ± 0.2 seconds. During a simulated 34-minute network outage test, the local edge-buffering mechanism effectively queued the disconnected telemetry. Upon reconnection, the deferred synchronisation protocol successfully recovered the data, resulting in 92.38% of the total records being pushed via buffered uploads, as summarised in Table 2. This mechanism prevented a 28.23% permanent data loss rate that would have otherwise occurred in traditional, unbuffered cloud architectures, thereby confirming the framework's robustness against real-world connectivity fluctuations.

Second, the operational reliability of the mobile AR interface was evaluated by logging and classifying 102 user touch interactions during unguided pilot testing. The rule-based mistouch detection algorithm utilised strict heuristic constraints, invalidating interactions that exceeded a spatial movement of 25 pixels (Parhi et al., 2006) or a temporal duration of 400 milliseconds (Cockburn et al., 2019). As detailed in Table 3, the classification results revealed that 62.75% of inputs were intentional commands, while 37.25% were flagged as accidental mistouches, which

Table 2
Real-time vs buffered data upload summary

Metric	Count	Percentage
Real-Time Uploads	8	7.62%
Buffered Uploads	97	92.38%
Total Records Pushed	105	100%

Table 3
Rule-based classification summary

Classification Type	Count	Percentage
Intentional Touch	64	62.75%
Mistouch	38	37.25%
Total	102	100%

were characterised by longer mean durations of 0.44 seconds and erratic movement trajectories averaging 67.30 pixels. While a 37.25% mistouch, rate is significantly higher than standard 2D mobile benchmarks, this metric critically reflects the steep spatial learning curve novice users face in unguided AR environments rather than an algorithmic failure. Crucially, the algorithm succeeded in its primary objective by intercepting these 38 accidental events, ensuring that resting touches and inadvertent swipes did not trigger unintentional physical actuations within the aquaponics hardware.

Third, the accuracy of the predictive fallback mechanism was rigorously quantified using standard statistical error measures, specifically MSE, RMSE, MAE, and R^2 (Chicco et al., 2021). As outlined in Table 4, the slope-only simple linear regression model demonstrated high predictive strength when applied to dynamic environmental parameters. For example, water temperature and air humidity forecasts yielded exceptional R^2 values of 0.9898 and 0.9858, respectively, confirming the model's reliability in sustaining data visualisation for fluctuating variables during short-term sensor outages. However, the analysis also exposed a critical algorithmic limitation when applied to low-variance parameters. The water level sensor yielded a negative R^2 value of -1.0033, demonstrating that the trend-seeking nature of linear regression performs worse than a naive mean predictor when applied to near-static data. This unexpected observation indicates that future DT implementations must adopt parameter-specific forecasting strategies, utilising static state monitoring rather than regression models for stable environmental thresholds.

Table 4
Performance metrics of the predictive model across sensor fields

Field	MSE	RMSE	MAE	R^2
pH	0.071	0.2665	0.0559	0.6334
WaterTemp	0.0524	0.2289	0.0373	0.9898
AirTemp	0.0775	0.2784	0.0462	0.9896
AirHumidity	0.3522	0.5935	0.1464	0.9858
LightIntensity	566.4417	23.8	3.6573	0.9102
WaterLevel	0.0223	0.1493	0.0086	-1.0033
WaterQuality	170.7588	13.0675	1.5537	0.1703

User Acceptance Testing and Usability Evaluation

Following the technical validation, the holistic usability and user satisfaction of the system were evaluated through a UAT. As illustrated in Figure 6, the UAT was conducted to assess the DTIAR aquaponics system's functionality, usability, and user satisfaction. The evaluation took place in Multimedia Laboratory 1 at the Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, involving 50 undergraduate and postgraduate participants who were either familiar with aquaponics or had no prior experience with the system. Participants received a real-time system demonstration followed by hands-on opportunities with the DT-AR application, after which data were collected using a structured survey to gather quantitative and qualitative insights regarding system performance, usability, and user experience.

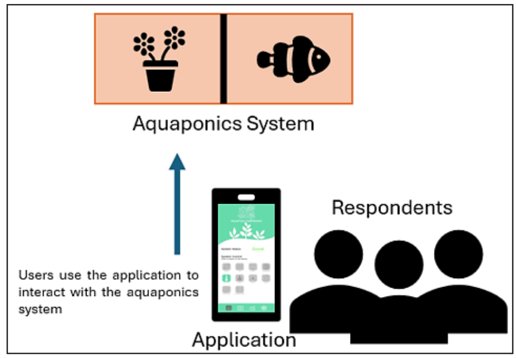

Figure 6. Method during UAT

Respondent demographics, as summarised in Figure 7, revealed a predominantly young adult population aged 20 and 21 years old, representing 32% and 24% of the cohort respectively, forming a digitally literate group well-suited for AR smart farming systems.

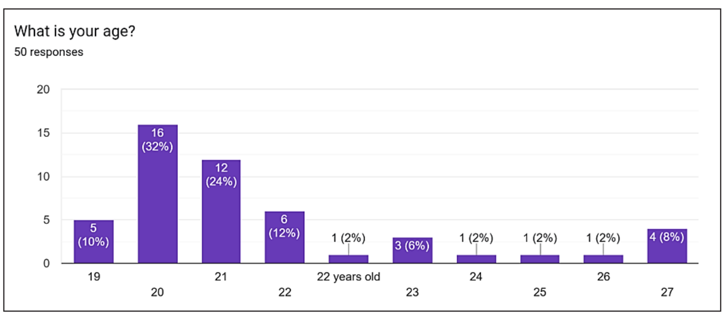

Figure 7. Demographic respondents

Regarding prior exposure to augmented reality, Figure 8 shows that 66% of participants reported previous experience with AR technology, while 34% were first-time users. This indicated that the interface needed to be flexible and intuitive enough to accommodate both novice users and those experienced with AR.

When evaluating preferred AR display modes in Figure 9, 56% of respondents favoured a simple AR display, while 40% preferred an overhead AR format for a more immersive experience.

Furthermore, as detailed in Figure 10, participants ranked the most desirable features of the application as visual quality (78%), interactivity (72%), and ease of use (68%), whereas mobile accessibility was preferred by 58%, and information richness was the least favoured feature at 32%, demonstrating that users prefer a visually clean interface over a cluttered data display.

Participants also evaluated acceptable price points for the system in Figure 11, with the largest group (approximately 25%) expecting a cost ranging from RM301 to RM500.

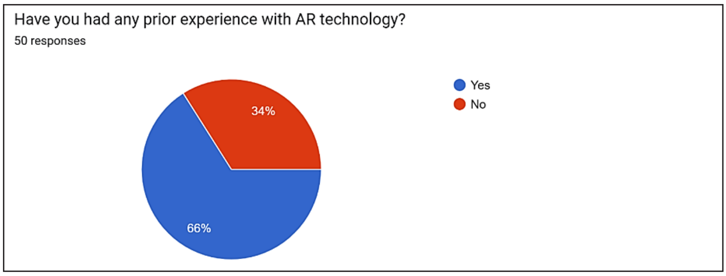

Figure 8. Respondents' experience with AR

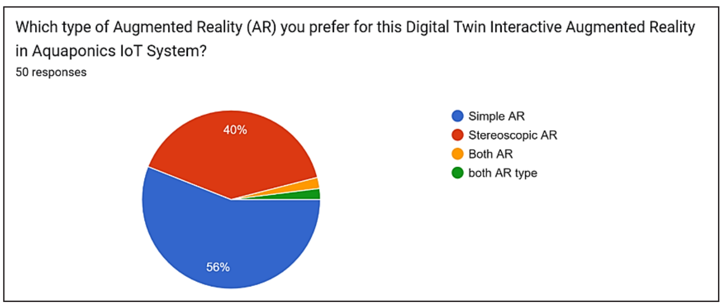

Figure 9. Type of AR respondents preferred

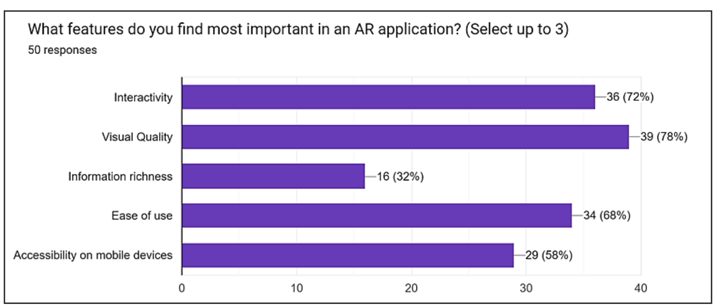

Figure 10. Features that respondents liked

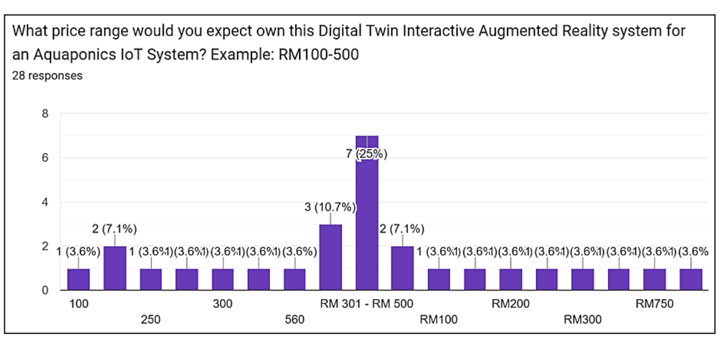

Figure 11. Expected cost of the system

In open-ended feedback shown in Figure 12, 15 respondents praised the interactive and engaging nature of the 3D animated models, with comments noting that stereoscopic AR offers a novel approach to future problem-solving.

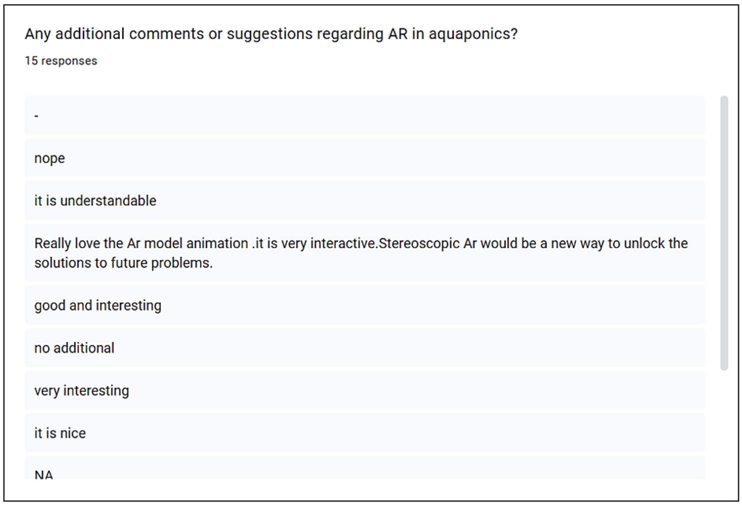

Figure 12. Comment from respondents

To complement these survey distributions with statistical rigour, Table 5 illustrated the quantitative usability analysis produced a mean SUS score of 56.63 with a standard deviation of ± 7.18, while the reliability of the instrument yielded a Cronbach's alpha of $\alpha = 0.63$. Although this SUS score falls into the marginal usability category according to established benchmarks, it sharply contrasts with the overall user satisfaction rate, where 85% of participants reported being satisfied or very satisfied with the platform. This discrepancy provides a critical insight: while users highly value the functional capabilities of the integrated AR and IoT system, the physical manipulation and spatial navigation required by the AR interface impose a high initial cognitive load. Overall, the UAT confirmed that the DT-AR aquaponics system provides an engaging, user-friendly experience that aligns with user expectations for digital smart agriculture management, while highlighting the necessity for future iterations to expand UI hitboxes and provide explicit onboarding cues.

Table 5
Summary of UAT metrics

Statistic	Value
Mean SUS Score	56.63
Standard Deviation	±7.18
Minimum SUS Score	42.5
Maximum SUS Score	70.0

Note. Cronbach's Alpha (α) = 0.630447046 ≈ 0.63

CONCLUSION

This study successfully designed, developed, and evaluated an integrated DTIAR framework to address the critical challenges of network instability, interaction reliability, and system resilience in smart aquaponic systems. By systematically bridging the technological silos between IoT hardware, cloud communications, augmented reality interfaces, and DT analytics, the research delivered a comprehensive management platform tailored for non-technical practitioners.

The technical evaluations confirmed the robustness of the proposed framework across its core objectives. The WebSocket communication architecture, paired with an edge-level local buffering and deferred synchronisation protocol, successfully achieved a 92.38% data recovery rate during network outages, effectively preventing the 28.23% data loss rate typical of unbuffered systems. Furthermore, the implementation of a rule-based mistouch detection algorithm governed by strict spatial movement and temporal duration thresholds successfully safeguarded the AR interface, intercepting 38 accidental touch events and preventing unintended hardware actuations during unguided navigation. The integration of a slope-only simple linear regression predictive fallback mechanism also demonstrated exceptional accuracy in sustaining data visualisation continuity for dynamic parameters such as water temperature $(R^2 = 0.9898)$ and air humidity $(R^2 = 0.9858)$ during short-term sensor disconnections.

Finally, the holistic usability and user satisfaction of the system were thoroughly validated through UAT. Engaging 50 diverse participants, the evaluation demonstrated that the platform delivers an engaging, immersive experience that aligns with user expectations for digital smart agriculture management. While the quantitative usability analysis yielded a marginal SUS score of 56.63, this was contrasted by an 85% overall user satisfaction rate, providing critical insight into the cognitive load associated with spatial AR navigation. Ultimately, this research provides a robust, fault-tolerant foundation for future smart farming innovations, offering clear pathways for enhancing interface accessibility and parameter-specific predictive modelling in agricultural technology.

FUTURE WORK

Building upon the foundational successes and identified limitations of the current DTIAR framework, several promising avenues remain for future research and system enhancement.

First, to address the performance limitations observed with low-variance parameters such as the negative R^2 value recorded for the water level sensor, future iterations of the DT intelligence layer should incorporate parameter-specific adaptive forecasting models. Rather than relying solely on linear regression, the system could dynamically switch between static state-monitoring algorithms for stable thresholds and advanced machine learning models (such as Long Short-Term Memory networks) for highly dynamic environmental metrics to improve overall prediction accuracy.

Second, given that the UAT revealed a marginal SUS score driven by the steep spatial learning curve of unguided AR navigation, future development should focus on enhancing interface ergonomics. This includes expanding interactive UI hitboxes, integrating haptic feedback cues, and implementing a guided, step-by-step interactive onboarding tutorial to actively reduce user cognitive load and minimise mistouches for novice practitioners.

Finally, future work should expand the physical deployment scope of the framework from controlled laboratory environments to large-scale, commercial multi-system agricultural setups. Testing the architecture across prolonged real-world deployments involving multiple distributed microcontrollers and concurrent user sessions will provide deeper insights into cloud scalability, long-term network resilience, and the economic viability of the platform for everyday urban farmers.

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LIST OF ABBREVIATIONS

Term	:	Definition
DT	:	Digital twin
AR	:	Augmented reality
IoT	:	Internet of Things
DTIAR	:	Digital twin interactive augmented reality
UAT	:	User acceptance testing
HCI	:	Human-computer interaction
SUS	:	System Usability Scale
MAE	:	Mean absolute error
MSE	:	Mean squared error
RMSE	:	Root mean squared error
R^2	:	Coefficient of determination
UI	:	User Interface

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