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A Multi-Layer Contextual Model for Managing Data Overload in Smart Hydroponics

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ABSTRACT

The widespread use of the Internet of Things (IoT) in hydroponic agriculture allows continuous monitoring of environmental conditions and provides real-time information to support crop management. However, the increasing amount of sensor data generated makes the monitoring process more complex as users need to interpret multiple environmental parameters simultaneously. Existing hydroponic monitoring systems focus on data collection and visualization, while the management and information delivery aspects to reduce data overload are still limited. This study proposes a multi-layer contextual model to manage environmental information in an intelligent hydroponic monitoring system. The model consists of five interconnected layers (Power, Sensor, Communication, Database and Visualization), which support the process of acquisition, validation, management and contextual data delivery. To validate the proposed model, a solar-powered IoT hydroponic monitoring system integrated with an Augmented Reality (AR) application was developed based on Situation Awareness Theory. Using the System Usability Scale (SUS), the prototype was assessed by three domain experts. The results achieved an average usability score of 85.83, which reflects excellent usability. The results indicate that the proposed model improves organisation and presentation of environmental information by prioritising contextually relevant data rather than displaying all available sensor readings at once. This enables users to identify important environmental conditions efficiently and supports more effective monitoring. This approach helps to reduce data overload and provides a practical framework that can support the development of IoT-based smart agriculture applications in the future through the integration of anomaly detection techniques and predictive analytics.

Keywords: Data overload, Situation Awareness Theory, Multi-Layer Contextual Model, Internet of Things (IoT), augmented reality.

INTRODUCTION

The rapid adoption of Internet of Things (IoT) technology has transformed hydroponic farming by enabling continuous monitoring of environmental conditions through interconnected sensors. Modern hydroponic systems can collect real-time information on parameters such as pH, temperature, humidity and water level, allowing growers to monitor crop conditions more efficiently and respond quickly to environmental changes. The integration of IoT with precision agriculture has been shown to improve productivity, sustainability and resource utilisation through data-driven decision-making (Kumari et al., 2024; Neri et al., 2025). However, the increasing number of sensors also generates a large volume of environmental data, creating new challenges in managing and interpreting information effectively. Although most IoT-based hydroponic systems are capable of collecting and transmitting data reliably, existing research has largely focused on hardware development, communication and automation, with less attention given to information management and presentation (Sportelli et al., 2025; Miller et al., 2025).

In practice, users rarely make decisions based on a single sensor reading. Instead, several parameters must be interpreted together to understand the overall condition of the hydroponic system. When all sensor readings are displayed simultaneously through conventional dashboards, users may experience information overload and increased cognitive load, making it more difficult to identify critical conditions that require immediate attention (Manono et al., 2026; Selvarajan, 2025; Stahmann et al., 2025). These limitations indicate that the effectiveness of a hydroponic monitoring system depends not only on accurate data collection but also on how information is organised and presented according to the monitoring context. Recent studies have highlighted the need for contextual visualisation and intuitive interfaces to improve information interpretation and support decision-making in smart agriculture (Kumari et al., 2024; Neri et al., 2025). Presenting only relevant information according to its priority can reduce information overload, improve situation awareness and enable users to respond more efficiently to environmental changes.

To address this gap, this study proposes a Five-Layer Model that provides a structured workflow for collecting, transmitting, managing and visualising environmental information before it is presented to users. In addition, Augmented Reality (AR) is employed to deliver contextual visualisation by overlaying digital information onto users' view of the real world (Mendoza-Ramirez et al., 2023), while the Contextual Information Prioritisation Algorithm (CIPA) prioritises sensor information based on the current monitoring context. By integrating information management with contextual visualisation, the proposed model aims to reduce information overload, improve system usability and support faster and more informed decision-making during hydroponic monitoring.

RELATED WORKS

Internet of Things and the Increasing Amount of Agricultural Data

The use of Internet of Things (IoT) technology has changed the way agricultural activities are monitored and managed. Monitoring in hydroponic farming has changed considerably with the adoption of IoT technology. Rather than depending solely on periodic manual observations, growers can continuously monitor their systems using interconnected sensors. These sensors measure essential environmental parameters such as pH, temperature, humidity, and nutrient concentration, providing timely information about changes that may affect plant growth. As stated by Dhanaraju et al. (2022) and Rofiansyah et al. (2025), continuous monitoring of the plant allows environmental changes to be detected earlier, which can reduce the risk of crop damage. In addition, it can also support a more accurate and effective decision-making process based on the data that has been gathered.

Continuous data collection has made hydroponic monitoring more effective, but it has also created a new challenge. As sensors operate throughout the day, they generate a constant flow of environmental information. While this provides a more complete picture of the growing environment, it also means users have to deal with much larger amounts of data than before. Each sensor contributes additional data that needs to be stored, processed, and interpreted before meaningful decisions can be made. Although these systems provide more detailed information, users often have difficulty identifying the most important information at the time it is needed (Laia et al., 2025). Therefore, the increased amount of sensor data can cause users to take longer to interpret the information before making a decision. In this regard, Laia et al. (2025) stated that the challenges in hydroponic systems have now shifted from simply acquiring data to managing the increasing amount of information more effectively. Recent studies have also shown a shift in focus in IoT-related research. Previous studies have focused more on technical feasibility such as sensor integration and wireless communication. On the other hand, more recent studies are beginning to recognize that the collection of environmental data in large quantities alone cannot necessarily improve the decision-making process. Without systematic management and information delivery, users may spend more time interpreting monitoring data than responding to actual changes occurring in the crop environment (En et al., 2026). This situation shows that information management has now become just as important as the process of data acquisition in the development of smart agricultural systems.

IoT-Based Hydroponic Monitoring System

Hydroponic farming requires close monitoring of environmental conditions because crop growth depends on optimal environmental balance. Parameters such as pH values, temperature, humidity, and water levels play an important role in influencing nutrient absorption as well as overall crop development. To reduce the need for manual monitoring, researchers are increasingly using IoT technology that allows these parameters to be continuously measured and monitored remotely. Most of the latest hydroponic monitoring systems integrate sensors with ESP8266 or ESP32 microcontrollers, cloud-based databases and web-based dashboards. The system has demonstrated good capabilities in environmental monitoring while providing real-time access to users through Internet-connected devices (Bouarroudj et al., 2025; Laia et al., 2025). These developments have improved the accessibility of information and reduced the burden of routine monitoring.

However, most existing systems are still focused on the process of data acquisition and communication. Its main objective is to ensure that sensor readings are collected and transmitted to the cloud platform accurately. On the other hand, less attention is given on how the information is organized before it is presented to the user. In most implementations, all sensor readings are displayed simultaneously through various graphs, tables, and numerical values, resulting in the user having to interpret a large amount of information before understanding the actual state of the hydroponic system. This situation becomes more complex when more sensors are added in the monitoring platform. While the addition of sensors increases the amount of information obtained, it also increases the user's load to interpret the data. Therefore, the effectiveness of a monitoring system does not only depend on its ability to collect environmental data, but also depends on the system's ability to organize and communicate information in a clear and easy-to-understand manner. Muhasin et al. (2024) also reached the same conclusion through a systematic study of smart hydroponic systems. Their findings show that most of the research emphasizes automation technologies, communication protocols and cloud connectivity, while aspects of information delivery, user interaction and long-term usability are still underpaid. This imbalance suggests that future research will need to place emphasis not only on technical development, but also on how users understand the information generated by IoT systems.

Data Overload in Hydroponic Monitoring

The rapid development of Internet of Things (IoT) technology has significantly increased the amount of information generated by smart agriculture systems. Continuous monitoring enables hydroponic systems to collect real-time environmental data from multiple sensors, improving crop monitoring, resource management, and operational efficiency (Kumari et al., 2024; Ahmed et al., 2025). However, the increasing number of sensors also generates a large volume of information that users must interpret during routine monitoring. When multiple sensor readings are displayed simultaneously, users may have difficulty identifying parameters that require immediate attention, leading to information overload, where excessive information can reduce rather than improve decision-making effectiveness (Ahmed et al., 2025; Sportelli et al., 2025). This produces data overload, which is a situation where too much information does not necessarily improve the quality of the decision-making process. In a hydroponic monitoring system, users typically need to compare several environmental parameters before determining whether corrective action should be taken. As the number of monitored parameters increases, so does the cognitive load of the user (Hou et al., 2025). Although the issue of data overload has been widely discussed in the field of information systems and human-computer interaction, studies related to this issue in the context of hydroponic monitoring are still limited (Ahmed et al., 2025; Sportelli et al., 2025). Most research evaluates systems based on sensor accuracy, communication performance or automation capabilities, while less attention has been paid to how environmental information is structured to support users during monitoring. Therefore, hydroponic monitoring systems in the future will need to not only produce accurate data, but also ensure that the information is presented systematically to reduce the complexity of monitoring without reducing the amount of information available.

Contextual Delivery of Information

The effectiveness of a monitoring system does not only depend on the accuracy of the data collected, but also on the way the information is presented to users. As more sensors are used in hydroponic systems, users will need to interpret a large number of environmental parameters simultaneously. While conventional dashboards provide access to all data, users often need to switch between various screens, graphs, and tables before understanding the actual state of the hydroponic system. This situation can disrupt the monitoring process and make it difficult for users to identify important changes, especially when several parameters need to be considered simultaneously (Tzounis et al., 2022). One approach to overcome this problem is through contextual information delivery. Instead of displaying all sensor readings through a separate interface, contextual systems only display information that is relevant to the object or situation being observed. This approach allows users to interpret information more naturally because digital content is directly linked to its physical context. Studies in the field of human-computer interaction show that contextual visualization can improve information awareness, reduce the need to navigate complex interfaces as well as accelerate the understanding of complex information (He et al., 2026; Rauschnabel et al., 2022;).

In agriculture, Augmented Reality (AR) is increasingly being explored as a technology that supports contextual visualization (Pallavicini & Anesa; 2026). By overlaying digital information on top of the real agricultural environment, AR allows users to view environmental information without having to switch between physical observation and a separate digital interface (Slimani et al., 2025). Previous studies have shown that AR has the potential to support crop monitoring, precision agriculture, agricultural training, and machine maintenance by displaying relevant information directly in the user's field of view (Benos et al., 2021; Barta et al., 2025). This approach not only improves the accessibility of information, but also creates a more intuitive interaction between consumers and the agricultural environment. Therefore, the integration of AR with IoT-based hydroponic monitoring systems is still

limited. Most studies focus more on technical aspects such as sensor integration, communication protocols and automation, while the use of AR to manage and present information from various IoT sensors is still poorly explored. Along with the increasing use of data in hydroponic systems, the delivery of information according to a physical context has the potential to reduce the complexity of interpreting various environmental parameters and consequently improve the user monitoring experience. This constraint is one of the main motivations for the development of the Multi-Layer Contextual Model based on Situation Awareness Theory, which is proposed in this study.

Situation Awareness Theory

Situation Awareness (SA) Theory was introduced by Endsley (1995) to explain how a person acquires, understands and uses information from the environment to support decision-making processes in dynamic situations. According to Endsley (1995), Situation Awareness is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future." This theory includes three main levels, namely perception, comprehension and projection (D'Aniello et al., 2026). At the perception level, the user acquires information from the environment, while comprehension involves the process of interpreting and understanding the information. Projection refers to the user's ability to anticipate future situations based on current information to support more effective actions and decisions. Originally, this theory was used in aviation, air traffic control, and the military, which require constant monitoring and rapid response. Nevertheless, the development of digital technology has expanded to fields such as smart manufacturing, robotics, Internet of Things (IoT) and smart agriculture (Patel et al., 2025). In smart agriculture, IoT allows data from various sensors to be collected in real-time, but the display of sensor readings alone still requires the user to interpret the state of the system on their own (Christias & Mocanu, 2026; Morchid et al., 2026). As the amount of data increases, users are at risk of information overload, thus making it difficult to identify information that is truly important. Based on this theory, this study proposes a Multi-Layer Contextual Model to support the formation of Situation Awareness. The Sensor Layer and Communication Layer support the level of perception through the collection and transmission of real-time data, while the Database Layer manages and organizes information before it is presented. Next, the Visualization Layer uses Augmented Reality (AR) technology to display information contextually to make it easier for users to understand the current state of the system and thus make more informed decisions. The relationship between Situation Awareness Theory and the Multi-Layer Contextual Model is shown in Table 1.

Table 1

Relationship between Situation Awareness Theory and the Multi-Layer Contextual Model

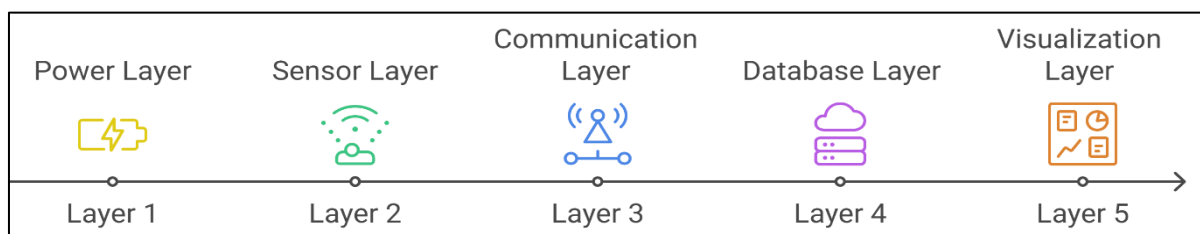
Situation awareness stage	Multi-layer contextual architecture	Role
Perception	Sensor Layer	Acquires real-time environmental data from IoT sensors.
Perception	Communication Layer	Transfers sensor data to the server.
Comprehension	Database Layer	Stores and manages collected data for processing.
Comprehension	Visualization Layer (AR)	Visualizes contextual information to improve user understanding.
Projection	User	Supports prediction and decision-making based on real-time information.
System Support	Power Layer	Provides power for continuous system operation.

The relationship between Situation Awareness Theory and the Multi-Layer Contextual Model forms the basis for the development of the proposed system and explains how the integration of IoT and AR can improve the effectiveness of hydroponic monitoring, reduce data overload problems and support faster and more accurate decision-making processes.

In summary, most previous studies have focused on sensor accuracy, communication reliability, automation and cloud connectivity. On the other hand, less attention is paid to how the increasing amount of environmental information affects users while carrying out routine monitoring activities. As more sensors are integrated into the hydroponic system, users need to interpret more and more environmental parameters simultaneously. While the increase in data provides a more comprehensive picture of the environmental conditions of crops, it can also increase the complexity of the monitoring process if all information is displayed without clear organization or priorities. This condition has the potential to increase the cognitive load of users as well as make it difficult for them to identify information that is truly critical for immediate action. Another constraint identified in the literature is that environmental information is typically displayed through conventional dashboards containing various graphs, numerical values and tables. While this interface provides comprehensive information, users often need to switch between various displays before they can understand the overall state of the hydroponic system. As a result, the challenges in monitoring systems are no longer only focused on the process of obtaining environmental data, but also involve how the information is structured and presented so that it can be interpreted quickly and support effective decision-making processes. In addition, most existing IoT architectures focus more on data collection, transmission, and storage, yet are still limited in how information should be managed and organised before it is presented to end users. In most studies, the visualization process is often thought of as the final output of the system rather than as an essential component of environmental information management. Therefore, the organization of information based on context and priority levels needs to be paid attention to so that the information displayed truly supports the needs of users during the monitoring process. To overcome these issues, this study proposes a Multi-Layer Contextual Model which consists of five main layers as shown in Figure 1.

Figure 1

Multi-Layer Contextual Model



The proposed model integrates these five layers into a systematic model to ensure that environmental data is collected, transmitted, stored, managed and presented contextually according to the user's requirements. This approach not only reduces data overload but also improves monitoring efficiency and enables faster, more accurate decision-making in smart hydroponic systems. Table 2 shows detailed descriptions of the proposed model.

Table 2

Proposed Multi-Layer Contextual Model

Proposed model	Focus	Main elements	Description
Multi-Layer Contextual Model with contextual visualization (AR)	Real-time hydroponics monitoring	Integrates sensing, communication, database management, and contextual visualization into a single framework. Organizes information before presentation and displays only relevant environmental data within the physical hydroponic environment, helping users interpret multiple sensor readings more efficiently.	The current implementation focuses on real-time monitoring. Future work will incorporate visual analytics, anomaly detection, predictive analytics, and personalized visualization to further support decision-making.

In contrast to the conventional Internet of Things (IoT) architecture, the proposed model sees information management as an ongoing process, from data acquisition to contextual information delivery. By organizing the flow of environmental information across interconnected layers, the model aims to manage the increasing amount of sensor data, reduce the complexity in interpreting various environmental parameters and improve the overall user experience when monitoring an intelligent hydroponic system. The next section describes the methodology used in this study.

THE PROPOSED METHOD

Overview of the Proposed Framework

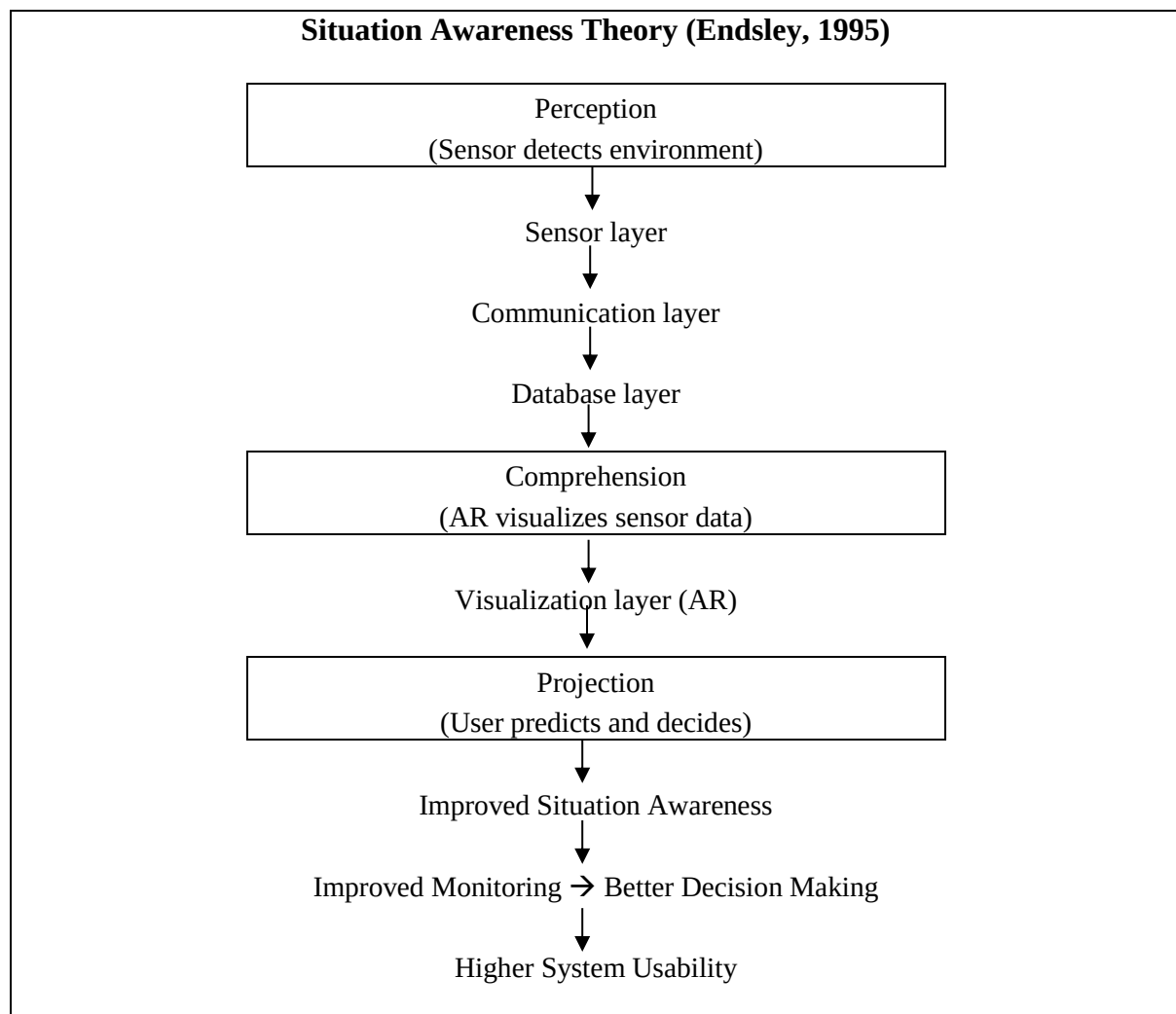
The increasing use of Internet of Things (IoT) technology in hydroponic agriculture has improved the efficiency of environmental monitoring through the continuous collection of sensor data. However, the collection of large amounts of environmental information alone will not necessarily improve the effectiveness of the monitoring process. A solution to this challenge requires more than just the development of another monitoring application. Instead, it requires a systematic model that can manage how environmental information is collected, organised, processed, and presented in a structured and easy-to-understand representation to users. The main contribution of this study is the development of a Multi-Layer Contextual Model to manage data overload problems in IoT-based hydroponic monitoring systems. Although the study also involved the development of IoT monitoring platforms and Augmented Reality (AR) applications, both technologies serve as proof of concept to validate the effectiveness of the proposed model rather than as the main contribution of the research. Therefore, the main focus of the study is on the design and evaluation of a model that integrates power management, environmental sensing, wireless communication, data management, and contextual visualization in a comprehensive model. Unlike most studies that focus solely on the development of IoT monitoring systems, this research focuses on the development of a Multi-Layer Contextual Model to manage data overload in hydroponic monitoring systems. The developed prototype serves as a platform to implement and validate the proposed model. Each phase produces an output that forms the basis for the next phase, thus ensuring that the final model is systematically developed and supported by theoretical and empirical evidence.

Multi-Layer Contextual Model

The proposed Multi-Layer Contextual Model organizes the hydroponic monitoring system into five interconnected layers. Unlike conventional approaches that treat each component as a stand-alone technology, this model treats each layer as part of a continuous information flow. Each layer performs a specific function while supporting processes on the next layer, thus ensuring that environmental data is systematically collected, transmitted, stored, and presented. This model also adapts the Situation Awareness Theory by Endsley (1995), which focuses on three main elements: perception, comprehension and projection. Figure 2 shows how Situation Awareness Theory integrates with the multi-layer contextual model.

Figure 2

Integration of Situation Awareness Theory with Multi-Layer Contextual Model



Layer 1: Power Layer

The Power Layer does not need to match any Situation Awareness Theory component because it is an infrastructure layer that supplies power to the entire system and does not directly affect the user's cognitive processes. Each layer in this model performs a different function to support the process of data collection, transmission, storage and visualization. Through this approach, users can perceive, comprehend, and use information more effectively when monitoring the hydroponic system.

Layer 2: Sensor Layer

The Sensor Layer collects environmental information from hydroponic systems and serves as the main data source in the proposed Multi-Layer Contextual Model. This layer consists of three sensing modules, as in Table 3.

Table 3

Sensing Modules

Sensor	Description
pH4502C	Measures the acidity and alkalinity levels of nutrient solutions
DHT11	Monitors the temperature and humidity of the environment
Water-level	Detects the amount of water in the hydroponic reservoir

The three sensors are connected to the ESP8266 NodeMCU microcontroller, which serves as the main processing unit for the monitoring platform. ESP8266 reads the sensor values at five-minute intervals and converts analogue and digital signals into structured data before sending them to the Communication Layer. Each reading includes a timestamp to maintain the chronological order of changes in environmental conditions, allowing historical records to be kept for future analysis. Regular data collection also ensures consistent monitoring and provides sufficient time resolution to identify trends and unusual changes in the hydroponic environment. In addition, the ESP8266 enables continuous data collection with low energy consumption and stable wireless communication. In the Multi-Layer Contextual Model, the Sensor Layer not only measures environmental parameters but also serves as the basis for the information management process by ensuring that only meaningful and relevant data enters the monitoring stream. The quality and relevance of the data collected at this stage directly influences the effectiveness of subsequent processes, including data transmission, database management, analysis, and contextual visualization. Therefore, the Sensor Layer plays an important role in managing data overload by filtering information early, reducing the accumulation of unnecessary variables, and ensuring that subsequent layers process only data relevant to hydroponic monitoring needs.

Layer 3: Communication Layer

The Communication Layer sends the environmental data collected by the Sensor Layer to a cloud-based database for storage and further processing. The NodeMCU ESP8266 uses a built-in Wi-Fi module to transmit readings from each sensor to a PHP-based web server. This web server uses the Hypertext Transfer Protocol, and it transmits data automatically. Every time the sensor sends a new reading, the data is stored in the database. This mechanism allows real-time data transmission based on the environmental data without the need for user intervention. The data that has been stored can be accessed through two methods, which are the web-based dashboards and Augmented Reality (AR) applications for monitoring purposes. Based on the Situation Awareness Theory, the communication layer supports the level of perception. The layer ensures that the data from the Sensor Layer is transmitted completely and accurately to the next layer. This quality information forms the basis for the comprehension process in the Visualization Layer. Algorithm 1 shows the algorithm used to verify sensor readings before sending data to the cloud server.

Algorithm 1: Sensor Data Validation

Input: pH, temperature, humidity, water level

Begin

1. Read sensor values from ESP8266
 pH $\leftarrow$ Read pH Sensor
 Temp $\leftarrow$ Read DHT11 Temperature
 Hum $\leftarrow$ Read DHT11 Humidity
 WL $\leftarrow$ Read Water Level Sensor
2. Check for missing values
 IF
 pH = NULL OR Temp = NULL OR Hum = NULL OR WL = NULL
 Reject Record
 STOP
3. Validate pH value
 IF
 pH < 0 OR pH > 14
 Reject Record
 STOP
4. Validate temperature
 IF
 Temp < -20 OR Temp > 70
 Reject Record
 STOP
5. Validate humidity
 IF
 Hum < 0 OR Hum > 100
 Reject Record
 STOP
6. Validate water level
 IF
 WL < 0
 Reject Record
 STOP
7. Check duplicate record
 IF
 Current Timestamp = Previous Timestamp AND Sensor Values are identical)
 Ignore Record
 STOP
8. Add Timestamp
9. Transmit validated record to PHP API
10. Store data in MySQL Database

End

Output: Valid sensor record transmitted to the database

Implementing data verification in the Communication Layer prevents corrupted, incomplete, or invalid data from being stored in the database. Only verified sensor readings will be sent to the next layer for storage and processing. This helps maintain data accuracy and reduces unnecessary entries in the system. By filtering out invalid data early, the next layer processes only complete, reliable information.

Layer 4: Database Layer

The Database layer serves as the primary repository for all environmental data received from the hydroponic monitoring system. After the Communication Layer verifies the data, the sensor readings are sent to a MySQL database hosted on a cloud server via a PHP-based web service. The database stores sensor readings in a structured format throughout the monitoring period, which facilitates the process of accessing, analysing and delivering information. This structure simplifies data retrieval, processing, and visualization. Each record contains the sensor type, timestamp, monitoring status, and alert level, as shown in Table 4.

Table 4

Database Table Structure

Record	Description
Sensor type	Distinguishes parameters such as pH, temperature, humidity, and water level
Timestamp	Records when each reading is received
Monitoring status	Indicates whether the hydroponic system is operating normally or requires attention
Alert level	Identifies readings that require immediate action

The database also maintains a history of all verified sensor readings. Historical records support the analysis of environmental changes over time, including pattern identification, comparison between monitoring periods, and trend observation. These records also support future functions such as anomaly detection and predictive analysis. The Database Layer supports the level of comprehension in Situation Awareness Theory, where this layer provides compiled data that is given context before it is displayed to the user. Here, the structured information enables the process of understanding the current state of the hydroponic system and forms the basis for the visualization process in the Visualization Layer. The user can clearly understand the system state, enabling more informed decisions. By contextually classifying information during data storage, the Database Layer no longer functions simply as a data storage medium, as in conventional systems. Instead, this layer acts as an information management component that provides environmental data for contextual visualization processes. Therefore, the Visualization Layer does not need to obtain all available sensor readings during the monitoring process, but instead only accesses information based on a predetermined level of priority and monitoring context. This systematic organization of information reduces access to unnecessary data, reduces the display of excessive information, and helps users focus on environmental conditions that require immediate action. In this study, the Database Layer compiles and manages data that has been verified before it is sent to the Visualization Layer.

Layer 5: Visualization Layer

The Visualization Layer is the final layer in the proposed Multi-Layer Contextual Model. It collects and organizes data from the previous layer into a simplified form for the user. To visualize the data, firstly, the information is gathered from the database. The data can be displayed through two interfaces (Web-based dashboard and AR application). The web-based dashboard can display more detailed information, such as historical records, graphs, and sensor-reading trends, while the AR application displays only the current monitoring information. The visualization process begins when the system obtains the latest sensor readings from the database. Then, each reading is divided into three statuses (Normal, Warning

and Critical) based on the predetermined range of hydroponic operation using the Contextual Information Prioritization Algorithm (CIPA), shown as Algorithm 2. The display prioritises readings classified as Critical. For example, low water levels or out-of-range pH values are classified as Critical. During routine monitoring, the system displays only current information. In the AR applications, the system displays only information related to the hydroponic component being observed. For example, when the smartphone camera is pointed at the image target, the application displays the system's current pH value, water level, temperature, and humidity. The AR view does not display historical information or graphs, but users can access them through a web-based dashboard. This approach simplifies the display and helps users focus on the information that matters during monitoring.

This layer implements the CIPA to determine the information that is displayed to the user. This layer implements the CIPA algorithm to classify verified sensor readings according to predefined hydroponic operating thresholds. Instead of treating every reading equally, the algorithm assigns priority levels where readings within the normal operating range are labelled Normal, while readings approaching the threshold are classified as Warning. Readings beyond the critical threshold are labelled Critical and assigned the highest display priority. CIPA does not discard data, but it only prioritizes the information presented to users according to the algorithm below. As a result, users can identify critical environmental conditions without reviewing every sensor reading.

Algorithm 2: Contextual Information Prioritization Algorithm

Input: Validated Sensor Data

Begin

 For each validated sensor record

 Store Timestamp

 Determine Monitoring Status

 IF pH < 5.5 OR pH > 6.5

 Status ← Warning

 ELSE

 Status ← Normal

 IF Water Level < Minimum Threshold

 Status ← Critical

 IF Temperature Out of Acceptable Range

 Status ← Warning

 Assign Alert Level

 Critical → High Priority

 Warning → Medium Priority

 Normal → Low Priority

 Save

 Sensor Type

 Sensor Value

 Timestamp

 Monitoring Status

 Alert Level

End For

Return Structured Environmental Information

Output: Structured Environmental Information

An AR application is developed using Unity and Vuforia Engine as the image recognition engine. The AR view does not display supporting information such as historical graphs, previous reading records, and communication status, but users can still access it through the web-based dashboard as shown in Figure 3.

Figure 3

Web-based Dashboard



The target image as shown in Figure 4 is used as a marker to identify a hydroponic system. When a mobile device's camera detects a preset target image, the AR application will retrieve the latest environmental information from the database.

Figure 4

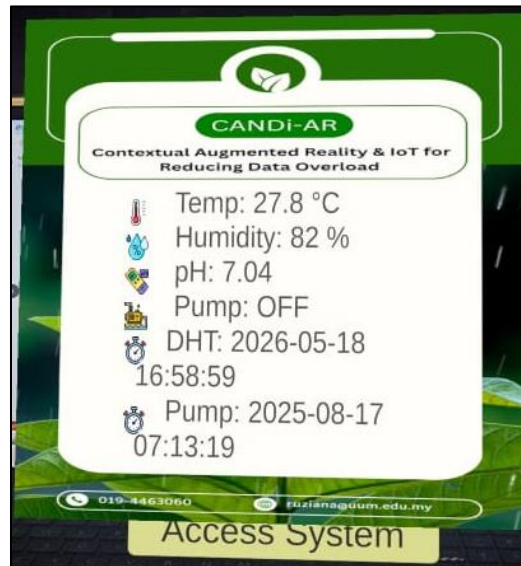
Target Image



The database includes pH values, temperature, humidity, water levels, monitoring status, and current alert levels. The system then displays these data as a virtual object placed in a position corresponding to the real hydroponic system in real time, as shown in Figure 5. Users can view the physical condition of the hydroponic system and environmental information simultaneously without switching between observations of the actual system. The AR application displays only information related to the hydroponic components being observed, reducing unnecessary information. This contextual delivery makes it easier for users to understand the current system state quickly and identify parameters that need attention.

Figure 5

The Augmented Reality Application



From the perspective of Situation Awareness Theory, AR applications support comprehension by displaying information in the context of the real environment, making it easier for users to interpret the current state of the hydroponic system. The information displayed also helps users anticipate changes and determine appropriate actions, in line with the level of projection. This approach supports the main objective of the Multi-Layer Contextual Model: to systematically manage information before presenting it to users, reducing data overload and improving the effectiveness of monitoring and decision-making. Contextually displaying information helps users understand the current state of the system more easily. The AR application complements the Visualisation Layer function in the Multi-Layer Contextual Model and supports a clearer, organised, and easy-to-understand hydroponic monitoring process.

Assessment using System Usability Scale

The final phase of this study focuses on evaluating the usability of the developed prototype using SUS. The main objectives of this evaluation are to determine whether the developed system can help users monitor hydroponic conditions more easily and also assess the user's experience while using the system. In contrast to assessments that focus only on sensor performance or network communications, this study assesses how users interact with the system as well as the extent to which the information displayed can help the monitoring process. Although this study uses the System Usability Scale (SUS) as an assessment instrument, the findings also provide insight into the system's ability to support the formation of Situation Awareness during the monitoring process. The System Usability Scale (SUS) was chosen because it is one of the most widely used instruments for assessing the usability of interactive systems. It is suitable for use despite involving a small number of participants. Therefore, this instrument is suitable to be used to evaluate the prototypes developed in this study. The System Usability Scale (SUS) questionnaire contains 10 statements used to assess the system's overall usability. Each statement is answered using a five-point Likert scale, which ranges from 1 (Strongly Disagree) to 5 (Strongly Agree). This questionnaire includes a mix of positive and negative statements to reduce participants' tendency to give the same answer for each item. All SUS statements used in this study are shown in Table 5.

Table 5*System Usability Scale (SUS) Questionnaire*

No.	Statement
Q1	I think that I would like to use this system frequently.
Q2	I found the system unnecessarily complex.
Q3	I thought the system was easy to use.
Q4	I think that I would need the support of a technical person to use this system.
Q5	I found the various functions in this system were well integrated.
Q6	I thought there was too much inconsistency in this system.
Q7	I would imagine that most people would learn to use this system very quickly.
Q8	I found the system very cumbersome to use.
Q9	I felt very confident using the system.
Q10	I needed to learn a lot of things before I could get going with this system.

For statements that are positive (Questions 1, 3, 5, 7 and 9), one point is subtracted from the response score. For negative statements (Questions 2, 4, 6, 8 and 10), participants' response scores were subtracted from five. This scoring method converts each question score to a range of 0 to 4, ensuring that a higher score always reflects better system usability, regardless of whether the statement is positive or negative. Next, add the adjusted scores for all ten statements to obtain the total score. Then multiply the total score by 2.5 to obtain a final SUS score from 0 to 100, where a higher score indicates better system usability based on user perception. The method of calculating the SUS score is shown in Equation 1:

$$\text{Score} = \left(\sum_{i=1}^{10} S_i \right) \times 2.5 \quad (1)$$

where:

S_i represents the adjusted score for each questionnaire item.

The maximum possible SUS score is 100.

In general, a SUS score above 68 indicates a satisfactory level of usability, while a score above 80 is usually interpreted as indicating excellent usability and high user acceptance (Bangor et al., 2008). Therefore, this study involved field experts to evaluate the usability of the prototype developed based on the Multi-Layer Contextual Model. This assessment aims to determine how easy the proposed system is to use, how effectively it supports the hydroponic monitoring process, and how it improves the user experience through contextual information delivery. The next section discusses the usability assessment findings based on the SUS score.

RESULTS

The feasibility of the proposed AR-based hydroponic application was evaluated using SUS involving three field experts. Respondents included an expert in AR application development, an expert in web system development, and an expert in hydroponics. Each expert was given time to use all system

functions, including monitoring data through a web-based dashboard and using an AR app to view hydroponic information in real time. Throughout the evaluation session, participants carried out several monitoring activities as is common in hydroponic operations. This approach allows participants to assess how the system supports information acquisition, understand the current state, and make decisions while using the system. The usability assessment results show that the system obtained a SUS score of 85.83. Based on the literature review, this value indicates that the system has excellent usability. In relation to the Situation Awareness Theory, this score shows that users can easily obtain information from the system (perception), understand hydroponic conditions through AR visualisation (comprehension), and use the information to make appropriate decisions (projections). These findings prove that the use of AR technology in the Visualization Layer successfully improves the effectiveness of information delivery and supports the main objective of the study, which is to reduce the problem of data overload and improve the efficiency of hydroponic monitoring. Table 6 shows the detailed feedback gathered by the expert.

Table 6

Expert's Feedback

Expert	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	SUS Score
Expert 1	5	1	5	1	5	1	5	2	4	1	95
Expert 2	5	1	5	4	5	1	5	1	5	4	85
Expert 3	4	1	4	4	5	1	4	1	5	4	77.5

Based on the SUS interpretation scale, two respondents rated the app in the Excellent category, while one respondent rated it in the Good category. These findings show that the developed app provides a positive user experience and is generally well received. Analysis of individual responses to the SUS questionnaire also showed a consistent pattern. All three respondents agreed that the app is easy to use, its functions are well integrated and users can learn how to operate it in a short period of time. Most respondents also disagreed that the app is overly complex or inconsistent, indicating that its interface design is clear, simple, and easy to understand. In addition, they expressed confidence when using the app, showing that integrating AR technology with real-time hydroponic data does not add unnecessary complexity for users.

Based on the feedback received, a high SUS score indicates that delivering environmental information through the Multi-Layer Contextual Model supports an effective monitoring experience. Participants can easily access relevant hydroponic information without dealing with excessive interface complexity. These findings suggest that the proposed model reduces data overload during routine monitoring while making it easier for users to identify information important for decision-making. Although the number of evaluators in this study was small, the involvement of field experts was consistent with the objective of the study, which was to confirm the level of usability of the prototype developed rather than making generalizations about the level of user acceptance in the larger population. Here, the findings provide preliminary evidence that the proposed model is a practical approach with the potential to manage and present environmental information more systematically in an IoT-based hydroponic monitoring system. The experts also provided feedback and suggestions for improving the developed system. This feedback helps identify strengths and areas for future improvement. Table 7 lists the feedback provided by experts during the usability assessment process.

Table 7

Additional Expert's Feedback and Suggestions

Expert	Comments
Expert 1	1) Ease of use.
Expert 2	1) Information from the AR application helps retrieved hydroponics data in real time.
Expert 3	1) The combination between AR and IoT make the hydroponics interesting. 2) Provide more features on the AR application that could help farmers work more efficiently.

Expert feedback shows that the developed AR-IoT hydroponic application has received positive evaluations. The application is easy to use, capable of acquiring and visualizing hydroponic data in real-time, and successfully integrates AR technology with the IoT to produce a more interactive and engaging monitoring experience. They also argue that combining AR and IoT creates a more engaging, interactive, and intuitive monitoring experience than conventional systems that rely solely on dashboard displays. While overall feedback was overwhelmingly positive, respondents suggested further enhancing the app by adding new functions to better support farmers' daily monitoring activities. These recommendations indicate that the prototypes provide a solid foundation, while future improvements could focus on expanding the system's functionality to better meet real needs in agricultural practices. Overall, the usability assessment shows that the proposed AR hydroponic application is intuitive, easy to learn, and effective in delivering hydroponic information contextually. A high SUS score, along with positive qualitative feedback, shows that the Multi-Layer Contextual Design Model supports the development of user-friendly AR-IoT applications while reducing data overload and improving the effectiveness of real-time hydroponic monitoring.

CONCLUSION

The findings show that the effectiveness of hydroponic monitoring systems depends not only on the ability to collect data in real time, but also on how the information is managed and presented to users. The growing demand for Internet of Things (IoT) technology has increased the amount of data generated, making it difficult for users to identify what is truly important when all readings are displayed at once. In line with Situation Awareness Theory (Endsley, 1995), an effective system needs to help users acquire, understand and use information to make decisions. Therefore, the proposed Multi-Layer Contextual Model manages the flow of information in stages, starting from data collection, transmission, and storage to AR visualization. Through the Contextual Information Prioritisation Algorithm, the system displays only relevant information based on priority level, reducing data overload, facilitating monitoring, and improving users' understanding of the hydroponic system's current state. This study contributed to developing an information management model that combines Situation Awareness Theory with the Multi-Layer Contextual Model to support IoT-based hydroponic monitoring. In contrast to most previous studies that focused more on hardware development and data collection, this study emphasizes the contextual organization and delivery of information. Although the usability assessment received positive feedback, the study remained limited to a prototype evaluated by three experts and covered only a few key hydroponic parameters. In the future, this model can be extended to other smart agriculture applications such as greenhouses, aquaculture, and smart irrigation systems, and enhanced with techniques such as machine learning, anomaly detection, and predictive analytics to support more effective monitoring and decision-making.

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