AGRI XR HYDRO TWIN: INNOVATING FUTURE FARMING WITH DATA DRIVEN METAVERSE

[1]Kunal S. Patil, [2]Naresh A. Kamble,

[1]Student, [2]Assistant Professor,
[1]Department of Computer Science & Engineering,
[1]D.Y. Patil Agriculture & Technical University, Kolhapur, India

Abstract : As cities expand and the land available for conventional farming shrinks, soilless growing methods such as hydroponics have drawn renewed attention as a way to keep food production close to where people live. Running a hydroponic system well, however, depends on tracking nutrient concentration, pH, and several environmental variables at once, a task that most beginners find hard to learn from a conventional two dimensional dashboard. This paper sets out a framework, Agri XR Hydro Twin, that links Internet of Things (IoT) sensing, digital twin modeling, and extended reality (XR) so that a physical hydroponic system can be viewed and manipulated as an interactive three dimensional model. The same digital twin is then placed inside a shared metaverse space, where a conversational AI assistant and a set of gamified tasks are meant to help newcomers learn the system without outside guidance. The paper surveys prior research on agricultural digital twins, immersive data visualization, and gamified training platforms, identifies where this research leaves a gap, and proposes a four layer architecture, physical hydroponics, cloud and IoT connectivity, the digital twin, and the immersive XR and gamified learning interface, to close it. Literature comparison, system diagrams, and a working data pipeline description are provided to support the design.

IndexTerms - **smart agriculture, precision hydroponics, digital twin, extended reality, metaverse, gamification.**

I. Introduction

Cities keep growing outward, and the land that once supported conventional farming is steadily converted to other uses. That trend, combined with rising concern over food security and the sustainable use of water and nutrients, has pushed growers toward controlled environment methods, hydroponics among them. A hydroponic system feeds plants through a nutrient rich water solution instead of soil, and the result is usually faster growth, lower water use, and fewer soil borne diseases, all within a much smaller footprint than a conventional field. These properties make the method a natural fit for terraces and rooftops in dense urban settings.

Running such a system reliably is not simply a matter of installing pipes and pumps. IoT sensors that track pH, electrical conductivity, temperature, and light intensity, paired with automated dosing hardware, have made it possible to keep these variables within range without constant manual checking. Digital twin technology takes this a step further by building a three dimensional virtual model of the farm that stays synchronized with live sensor data, and extended reality (XR) platforms extend the idea again, placing that model inside a shared virtual space where farming tasks can be rehearsed or observed without touching the physical system.

Even with these tools available, hydroponic management still calls for a working grasp of chemistry, plant physiology, and control logic that most newcomers simply do not have. The dashboards typically used to present this information rely on flat charts and numeric tables, and this separates a reading from the physical part of the system it describes, which makes the overall state of the farm harder to read at a glance. Agri XR Hydro Twin is built to close that gap: sensor values are attached directly to a virtual replica of the hydroponic setup, so checking on a pump, a reservoir, or a plant means looking at that object inside the virtual space rather than hunting through a separate screen. A gamified layer sits above this visualization, and a conversational AI assistant is included within it so that a new user can ask a question and keep working without stepping outside the immersive environment.

II. Literature Review

2.1 Digital twins in agriculture

Pylianidis et al. (2021) point out that digital twin methods, while well established in manufacturing, have mostly been applied to crop growth modeling in agriculture rather than to full system control. Verdouw et al. (2021) sort agricultural digital twins into three tiers, descriptive twins built for monitoring, predictive twins built for forecasting, and prescriptive twins built for decision making, and note that the bulk of existing systems stop at the descriptive tier. The underlying concept traces back to Grieves and Vickers (2017), who describe a digital twin as a two way channel of information between a physical asset and a virtual model of it. Neethirajan and Kemp (2021), working in livestock farming, report that an edge computing setup can keep sensor and twin synchronized to within a fraction of a second, a result that matters directly for any XR application that needs to feel responsive.

2.2 Hydroponics and controlled environment agriculture

Resh (2012) lays out the established hydroponic families, nutrient film technique, deep water culture, and aeroponics, in detail. Domingues et al. (2012) found that automated pH and electrical conductivity control raised lettuce yields by 25 to 40 percent compared with soil grown crops. Sivakumar et al. (2020) built an IoT monitoring setup around ESP32 microcontrollers and reported pH and EC accuracy near 98 percent, and Saaid et al. (2015) demonstrated an automated dosing system for deep water culture that responds to sensor feedback and cuts down on manual correction. Santosh and Gaikwad (2023) offer a broader survey of hydroponic system types and their management needs.

2.3 Extended reality for data visualization

Ens et al. (2019) and Chandler et al. (2015) both find that showing data in three dimensions, an approach usually labeled immersive analytics, helps people read spatial datasets and spot patterns faster than they would with a standard two dimensional chart, with Chandler et al. reporting roughly a 43 percent speed gain. Dey et al. (2018) reviewed augmented reality work in precision agriculture, where crop health data is overlaid on a real field through a phone or tablet screen. Mourtzis et al. (2020) found that VR based training shortened the time needed to pick up new operating skills in an industrial setting, and Bach et al. (2018) proposed treating statistical values as objects a user can grab and move within a virtual scene, an idea this project borrows directly for representing hydroponic readings. Evangelos, Athanasios, and Spyros (2023) survey XR use across agriculture, livestock, and aquaculture more broadly and note that hydroponic specific applications remain rare, which is the gap this project targets.

2.4 Gamification and metaverse learning environments

Dicheva et al. (2015) and Hamari et al. (2014) both report clear engagement gains from gamification elements such as points, leaderboards, and simulation challenges, with Hamari et al. finding a positive learning effect in 74 percent of the empirical studies they reviewed. Blackmore et al. (2016) looked at agricultural simulation titles such as Farming Simulator and concluded that, while they build a general sense of crop management, their nutrient modeling is not realistic. Lee et al. (2021) define the metaverse as a persistent, shared space that connects physical and digital experience, and Wang et al. (2022) report that metaverse based vocational training in manufacturing cut training time by 40 percent while raising knowledge retention by 55 percent relative to conventional instruction. Krishnan et al. (2024) discuss the wider potential of metaverse applications in agriculture.

2.5 Game engines for scientific and data visualization

Newer versions of Unreal Engine bring rendering methods such as Nanite virtualized geometry and Lumen global illumination that support fine, real time detail without the polygon limits older engines imposed (Karis, 2021; Epic Games, 2024). These tools already appear in architectural and film work, and Thompson et al. (2019) and Marks et al. (2020) show the same rendering pipeline handling live oceanographic and medical datasets, well outside the entertainment context the engine was originally built for. That precedent is the main reason a game engine, rather than a conventional dashboard framework, was chosen as the rendering platform here.

2.6 Summary of the research gap

Taken together, the literature shows agricultural digital twins that are mostly descriptive and screen bound, XR studies that rarely touch hydroponic monitoring specifically, and gamified metaverse platforms that have not yet been tied to live IoT data. Agri XR Hydro Twin sits at the point where these three strands meet, connecting a physical hydroponic pilot to an XR digital twin housed inside a gamified, multi-user metaverse.

Table 1. Summary of the literature reviewed for this study

Source	Focus and method	Key finding	Relevance to present study
Pylianidis et al. (2021)	Review of agricultural digital twins	Digital twin methods are mature in manufacturing but limited mostly to crop growth modeling in agriculture	Motivates a twin that supports full spatial interaction rather than growth prediction alone
Verdouw et al. (2021)	Taxonomy of agricultural digital twins	Twins are classified as descriptive, predictive, or prescriptive; most current systems remain descriptive	Positions the present twin at the descriptive stage, with prescriptive control identified as future work
Grieves and Vickers (2017)	Conceptual foundation of digital twins	Defines a two way information exchange between a physical asset and its virtual counterpart	Provides the theoretical basis for linking sensor data to the virtual replica
Neethirajan and Kemp (2021)	Digital twins in livestock farming, edge computing	Sub second data synchronization is achievable using edge computing architectures	Supports the feasibility of a low latency IoT to XR pipeline
Resh (2012)	Reference guide to hydroponic techniques	Documents nutrient film technique, deep water culture, and aeroponics	Supplies the base hydroponic methods

Source	Focus and method	Key finding	Relevance to present study
			represented inside the digital twin
Domingues et al. (2012)	Automated pH and EC control, experimental	Automated nutrient control raised lettuce yield by 25 to 40 percent over soil based cultivation	Justifies including an automated control loop in the functional requirements
Sivakumar et al. (2020)	ESP32 based IoT hydroponic monitoring	Reported 98 percent accuracy in pH and EC sensing	Sets the sensor accuracy target used in the non-functional requirements
Saaid et al. (2015)	Automated nutrient dosing, deep water culture	Sensor driven dosing reduced the need for manual adjustment	Supports the design of the automated control layer
Ens et al. (2019); Chandler et al. (2015)	Immersive analytics, experimental studies	Three dimensional data display improved comprehension and raised pattern detection speed by about 43 percent	Justifies replacing flat dashboards with spatial data visualization
Dey et al. (2018)	Review of augmented reality in precision agriculture	AR overlays of crop health data are typically limited to mobile, screen based interaction	Highlights the narrower scope of AR alone relative to full XR immersion
Mourtzis et al. (2020)	VR based operator training, industrial case study	VR training shortened skill acquisition time relative to conventional instruction	Supports the use of VR for hydroponic operator training
Bach et al. (2018)	Human-computer interaction research on 3D data objects	Statistical values can be represented as manipulable three dimensional entities in virtual reality	Basis for the spatial, touchable representation of sensor readings
Evangelos, Athanasios, and Spyros (2023)	Review of XR across agriculture, livestock, and aquaculture	XR use is spreading across farming domains but hydroponic specific applications remain scarce	Confirms the research gap that this project addresses
Dicheva et al. (2015); Hamari et al. (2014)	Systematic reviews of gamification in education	Gamification raised engagement by 60 to 80 percent and improved outcomes in 74 percent of studies reviewed	Supports the inclusion of points, challenges, and badges in the metaverse layer
Blackmore et al. (2016)	Usability study of agricultural simulation games	Farming Simulator improves general understanding of crop management but lacks accurate nutrient modeling	Identifies the gap closed by linking real sensor data to gamified tasks
Lee et al. (2021)	Survey defining the metaverse concept	Describes the metaverse as a persistent, shared environment bridging physical and digital experience	Frames the shared, multi-user layer of the proposed architecture
Wang et al. (2022)	Survey of metaverse based vocational training	Metaverse training reduced training time by 40 percent and raised retention by 55 percent in manufacturing settings	Supports metaverse delivery for hydroponic skills training
Karis (2021); Epic Games (2024)	Technical documentation of Unreal Engine rendering	Nanite and Lumen allow detailed, real time rendering without conventional polygon budget limits	Supports the choice of a game engine as the rendering platform for the twin
Thompson et al. (2019); Marks et al. (2020)	Case studies of game engines for scientific and medical visualization	Game engines can render complex, live datasets in real time outside their original entertainment use case	Provides precedent for rendering live sensor data inside a game engine

III. PROBLEM STATEMENT

Hydroponic methods can support food production in cities without soil, but pairing them with sensor networks, digital twins, and XR is still mostly confined to specialist research settings and has not reached general practice. Three issues sit behind that gap.
First, the practical know how needed to run an urban hydroponic setup is not widely shared, and the supporting technologies, IoT, XR, and digital twins, remain opaque to practitioners and students who lack a technical background. Second, the monitoring tools in common use rely on flat screens and standard charts, which break a live system into disconnected numbers and make its overall behavior hard to follow. Third, current agricultural training resources rarely offer anything interactive or collaborative; specifically, no shared, multi user virtual space currently teaches hydroponic assembly and operation through gamified tasks tied to a digital twin.

IV. OBJECTIVES

Three objectives guide the project.
The first is to build an immersive digital twin of the hydroponic system, meaning a high fidelity, interactive three dimensional replica of the physical setup rather than a static model, so that a user can move through and inspect the system's layout directly. This replica becomes the base layer for the data and interaction features added afterward.
The second is to make live sensor data discoverable through an XR interface. Achieving this means building a working link between the physical IoT sensors and the digital twin, so that looking at a specific component, a pump or a plant, for example, shows its current state through a floating indicator or color code rather than through a separate table.
The third is to support learning through a gamified metaverse layer built around a conversational AI. The assistant is meant to work as a reference a user can consult by voice from inside the environment, without having to step outside to look something up. Paired with gamified tasks, this is intended to make independent exploration of precision hydroponics less intimidating for a first time user.

V. REQUIREMENT SPECIFICATION

5.1 Functional requirements

- Read environmental data from physical sensors, including water pH, electrical conductivity, temperature, and light intensity.
- Maintain a synchronized, two way link between the physical hydroponic setup and its digital twin.
- Include an automated control system that adjusts hydroponic parameters based on sensor readings.
- Provide an XR interface in which sensor data appears as floating indicators or color coded elements attached to the corresponding virtual components.
- Provide a gamified learning space with points, challenges, and virtual assistants to guide new users.
- Allow users to view and manipulate sensor data as three dimensional objects within the virtual environment.

5.2 Non-functional requirements

- Data synchronization latency should remain at sub second levels to keep the XR experience responsive.
- Sensor readings, particularly pH and electrical conductivity, should stay close to the 98 percent accuracy reported for comparable ESP32 based systems (Sivakumar et al., 2020).
- The interface should be usable by people without prior experience with hydroponics or XR hardware.
- The architecture should extend to different hydroponic methods, including nutrient film technique, deep water culture, and aeroponics.
- Telemetry must be transmitted securely from edge devices to the cloud database.

5.3 Hardware requirements

- A physical hydroponic setup, including tanks, pumps, and a nutrient delivery system.
- Sensors for pH, electrical conductivity, water temperature, light intensity, and humidity.
- Edge microcontrollers, such as ESP32 boards, to read sensor data and transmit it over standard internet protocols.
- XR output devices, including VR headsets or AR capable mobile devices.

5.4 Software requirements

- A game engine, Unity or Unreal Engine, for building the three dimensional environment.
- WebSocket or REST APIs for low latency telemetry transmission.
- A cloud database to store and serve sensor data to the XR interface.
- A conversational AI framework to support the virtual assistant.
- A web based XR delivery method to widen accessibility beyond dedicated hardware.

VI. System Architecture

The project's three objectives map onto three linked development strands, as summarized in Figure 1: the digital twin build feeds into engine level user experience design, the real time IoT to XR data link feeds into the visualization layer, and the gamified, conversational AI layer feeds into a knowledge base that users can query directly.

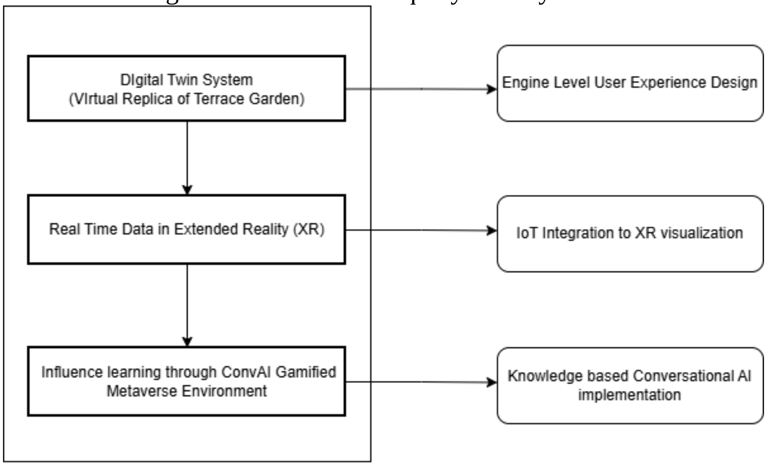

Figure 1. Overall project flow linking the three development strands to their supporting sub-systems

Underneath this flow sits a four layer architecture: physical hydroponics, cloud and IoT connectivity, the digital twin, and the immersive XR and gamified learning interface, shown in Figure 2.

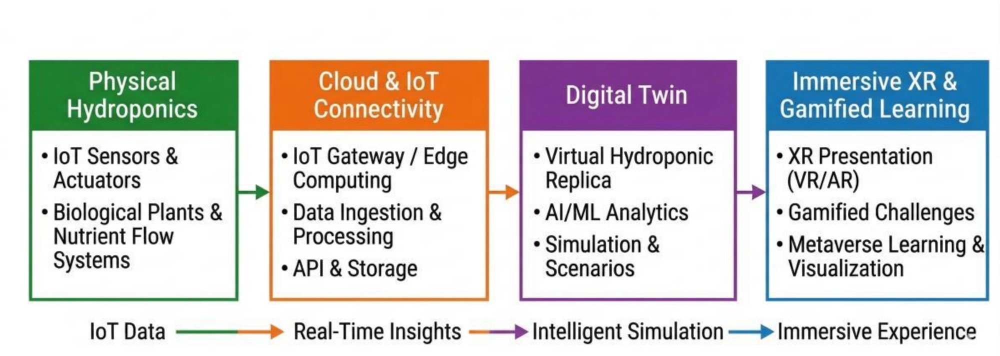

Figure 2. Four-layer system architecture connecting the physical hydroponic setup to the gamified XR interface

The physical hydroponics layer is a pilot setup, nutrient film technique, deep water culture, or aeroponic, fitted with sensors and actuators that track the biological and nutrient state of the plants. Microcontrollers at this layer read sensor values and pass them on over standard internet protocols.

The cloud and IoT connectivity layer takes in this telemetry over low latency channels, typically WebSockets or REST APIs, and stores it in a cloud database. This is also where the raw readings are cleaned and prepared before reaching the digital twin, and where the automated control logic for nutrient dosing and environmental adjustment lives.

The digital twin layer holds a virtual hydroponic replica that tracks incoming sensor data in close to real time. Basic analytics run at this layer as well, flagging a reading that falls outside a safe range or projecting where a given parameter is headed over the next short interval.

The immersive XR and gamified learning layer is where all of this becomes visible to a user. A sensor reading shows up as a floating label or a color coded marker on the matching 3D object, so an out of range pH value, for instance, appears directly on the reservoir instead of buried in a separate readout. This layer also holds the shared metaverse space, where several users can occupy the same environment at once, work through gamified tasks such as assembling a hydroponic system from its parts, and talk to a conversational AI assistant.

6.1 Building the digital twin

Building the digital twin proceeds through four steps, shown in Figure 3. The process starts by pinning down the twin's purpose, that is, which parameters and physical components it actually needs to represent. Next, the corresponding 3D models are produced or sourced, covering pieces such as nutrient reservoirs, PVC piping, and the different plant growth stages. The third step matches each modeled component to the dataset or data source that will drive it. The final step brings the assets and their data bindings together inside the chosen game engine, giving a spatially accurate replica that is also wired to live data.

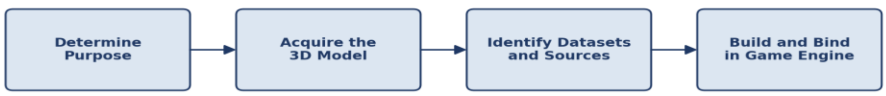

Figure 3. Four-step process used to build the digital twin

6.2 Data pipeline

The data pipeline starts at the sensor level, where edge microcontrollers collect pH, temperature, humidity, and related readings, as outlined in Figure 4. These devices push telemetry to a cloud database over WebSocket or REST connections chosen for their low latency. The XR environment then polls or subscribes to that database and updates the visual state of the matching 3D assets, keeping the spatial indicators close to the physical system with minimal lag.

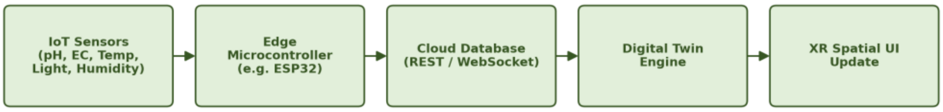

Figure 4. Data pipeline from physical sensors through the cloud layer to the XR interface

Figure 5 traces the same idea from the user's side: sensor data collected and stored in the database is fetched into the digital twin engine, after which a user inside the metaverse can either ask the AI assistant a question or work through a simulation task, with both paths feeding back into ongoing system monitoring and learning.

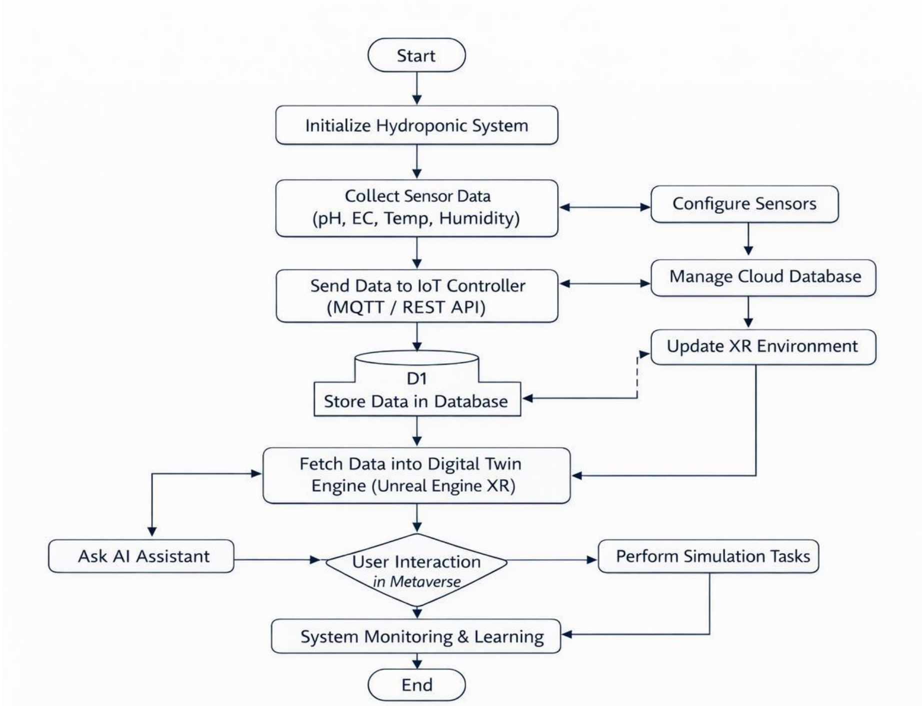

Figure 5. User-facing activity flow, from sensor data collection through digital twin interaction to learning outcomes

6.3 Gamified metaverse and conversational AI

The digital twin is extended into a shared, multi user metaverse through standard networking methods, so several people can occupy the same virtual space for collaborative learning. Inside that space, gamified tasks, locating and assembling missing components, or working through a guided maintenance scenario, are used to keep users engaged.

A conversational AI agent, built in this project on the Convai platform, sits above the environment as an on demand knowledge source. Figure 6 shows the interaction pipeline: a user's spoken input, picked up through a VR headset microphone, passes through a game engine integration plugin to a speech to text, language model, and text to speech chain, and returns to the engine for lip syncing and voice playback through a non player character. The assistant is meant to answer questions about hydroponic principles and current sensor readings without the user needing to leave the virtual environment.

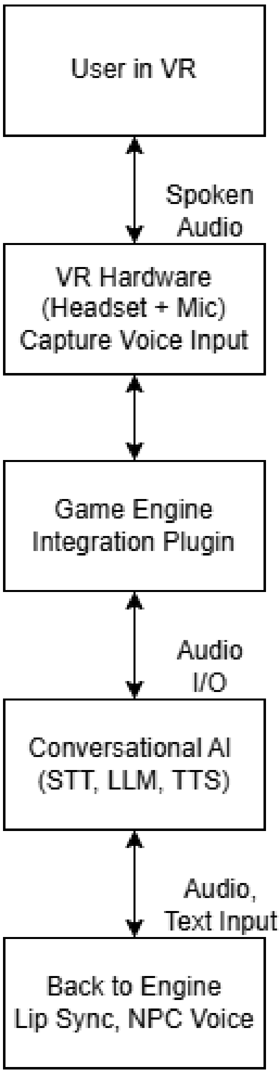

Figure 6. Interaction pipeline for the VR-based conversational AI assistant

6.4 Development snapshots

Figures 7 and 8 show early snapshots of the environment as modeled inside the game engine: a virtual hydroponics rack built from the reservoirs and channel geometry described in Section 6.1, and a wider view of the terrace garden setting in which the hydroponic zone sits alongside other planting areas.

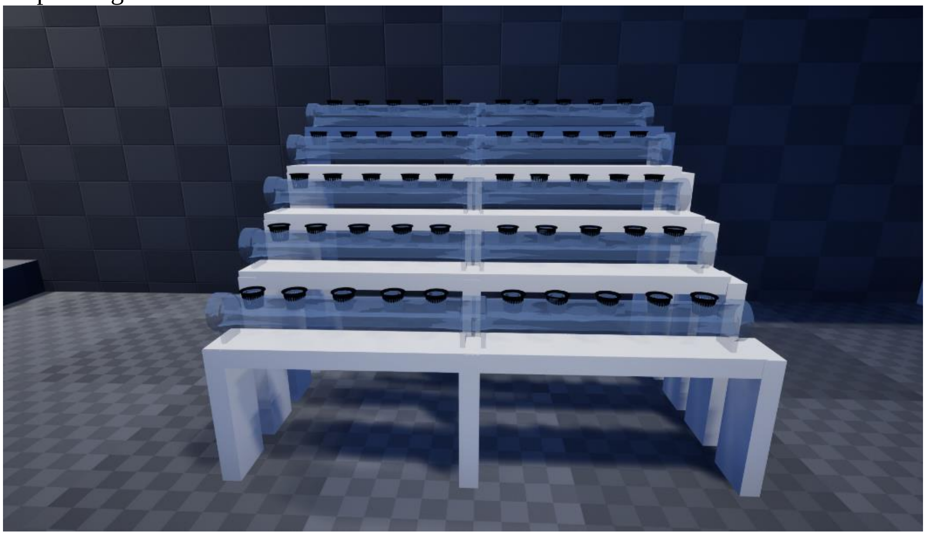

Figure 7. Virtual hydroponics rack modeled inside the game engine

Figure 8. Wider view of the modeled terrace garden environment

VII. Implementation Considerations

A responsive VR build of this kind leans on a handful of algorithms that are standard in XR development but worth summarizing here for completeness.

Tracking and spatial localization depend on simultaneous localization and mapping, or SLAM (Cadena et al., 2016), which builds a map of the physical room from the headset's camera feeds while working out the headset's own position inside that map. This is paired with sensor fusion methods such as the Kalman filter (Kalman, 1960), which blends fast but drift prone inertial readings with slower, more accurate optical tracking. Inverse kinematics is used separately to work out plausible arm and body poses for a user's avatar from the known positions of the head and hand controllers.

Rendering performance depends on keeping frame rates stable, since a dropped frame in VR translates almost directly into motion sickness. Asynchronous timewarp and spacewarp reuse or extrapolate the previous frame when the GPU cannot finish a new one in time. Foveated rendering, following Guenter et al. (2012), uses eye tracking to render only the point a user is actually looking at in full resolution while cutting detail toward the edges of view. Frustum and occlusion culling drop objects that fall outside the camera's field of view or sit behind other geometry, which lightens the rendering load in a densely modeled scene such as a hydroponic terrace garden.

Interaction and physics rely on raycasting, illustrated in Figure 9, which projects a line from the VR controller to work out which object or menu element it is pointing at, together with collision detection methods such as the Gilbert-Johnson-Keerthi algorithm (Gilbert, Johnson, & Keerthi, 1988), organized through bounding volume hierarchies so the engine only checks for collisions between objects close enough to plausibly touch.

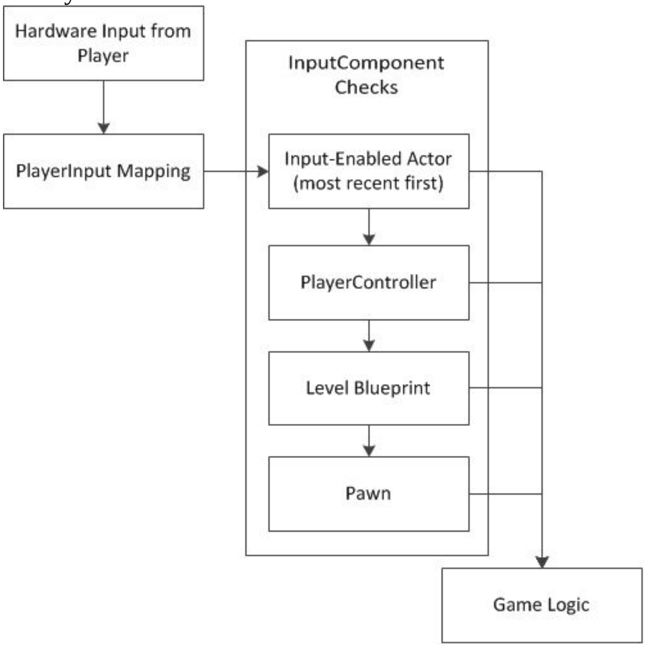

Figure 9. Input handling architecture used for VR controller interaction and game logic

Audio realism rests on head related transfer functions (Wenzel et al., 1993), which adjust a sound based on head orientation, distance from the source, and the acoustic shape of the human ear, letting a user judge the direction of a sound, a pump or an alarm, say, without turning to look at it.

VIII. Plan of Work

The project is organized into the following phases.

Table 2. Planned schedule of activities

Period	Planned activity
16 Aug 2025 to 30 Aug 2025	Problem definition, requirement gathering, and literature survey
30 Aug 2025 to 04 Oct 2025	Literature review, analysis, and system design
04 Oct 2025 to 01 Nov 2025	Partial implementation of the first module (digital twin)
01 Nov 2025 to 29 Nov 2025	Completion of the first module and partial implementation of the second module (IoT and XR data pipeline)
29 Nov 2025 to 31 Jan 2026	Full implementation of the second and third modules (data pipeline and gamified metaverse layer)
31 Jan 2026 to 07 Mar 2026	Module integration and system testing
07 Mar 2026 to 23 May 2026	Report and presentation preparation

IX. Conclusion and Future Work

Agri XR Hydro Twin brings IoT sensing, digital twin modeling, and extended reality together to move hydroponic monitoring away from fragmented two dimensional dashboards and toward a spatial view of the physical system. Layering a gamified, multi user metaverse and a conversational AI assistant on top of that view is meant to make the underlying technology, and precision hydroponics itself, less intimidating for students, urban growers, and researchers who do not come in with specialist training.

A few extensions follow naturally from the current design. Predictive and prescriptive capability could be added so the digital twin starts forecasting conditions and suggesting adjustments rather than only reporting what is happening now. The IoT pipeline, which at present only transmits data for display, could be linked to actuators so that nutrient dosing responds automatically to sensor readings without a person stepping in. A mobile augmented reality mode could carry the system beyond VR headsets, overlaying plant status directly onto physical crops through a phone or tablet camera. The gamification layer could also grow further, with more advanced scenarios aimed at users working toward professional level competence rather than general familiarity.

References

[1] Bach, B., Sicat, R., Beyer, J., Cordeil, M., & Pfister, H. (2018). The hologram in my hand: How effective is interactive exploration of 3D visualizations in immersive tangible augmented reality? IEEE Transactions on Visualization and Computer Graphics, 24(1), 457-467.

[2] Blackmore, H., Dogan, H., Bilham, A., & Apperley, M. (2016). Usability of educational software in agricultural domain: The case of Farming Simulator. Proceedings of the British HCI Conference, 1-6.

[3] Cadena, C., Carlone, L., Carrillo, H., Latif, Y., Scaramuzza, D., Neira, J., Reid, I., & Leonard, J. J. (2016). Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age. IEEE Transactions on Robotics, 32(6), 1309-1332.

[4] Chandler, T., Cordeil, M., Czauderna, T., Dwyer, T., Glowacki, J., Goncu, C., et al. (2015). Immersive analytics. Big Data Visual Analytics (BDVA), 1-8. IEEE.

[5] Dagar, R., Som, S., & Khatri, S. K. (2018). Smart farming: IoT in agriculture. Proceedings of the 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), 1052-1056.

[6] Dey, A., Billinghurst, M., Lindeman, R. W., & Swan, J. E. (2018). A systematic review of 10 years of augmented reality usability studies: 2005 to 2014. Frontiers in Robotics and AI, 5, 37.

[7] Dicheva, D., Dichev, C., Agre, G., & Angelova, G. (2015). Gamification in education: A systematic mapping study. Educational Technology & Society, 18(3), 75-88.

[8] Domingues, D. S., Takahashi, H. W., Camara, C. A., & Nixdorf, S. L. (2012). Automated system developed to control pH and concentration of nutrient solution evaluated in hydroponic lettuce production. Computers and Electronics in Agriculture, 84, 53-61.

[9] Ens, B., Lanir, J., Tang, A., Bateman, S., Lee, G., Piumarta, T., & Billinghurst, M. (2019). Revisiting collaboration through mixed reality: The evolution of groupware. International Journal of Human-Computer Studies, 131, 81-98.

[10] Epic Games. (2024). Unreal Engine 5.6 documentation: Nanite and Lumen rendering technologies. https://dev.epicgames.com/documentation/en-us/unreal-engine/

[11] Evangelos, A., Athanasios, T. B., & Spyros, F. (2023). Applications of extended reality (XR) in agriculture, livestock farming, and aquaculture: A review. Smart Agricultural Technology.

[12] Gilbert, E. G., Johnson, D. W., & Keerthi, S. S. (1988). A fast procedure for computing the distance between complex objects in three-dimensional space. IEEE Journal on Robotics and Automation, 4(2), 193-203.

[13] Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In Transdisciplinary Perspectives on Complex Systems (pp. 85-113). Springer.

[14] Guenter, B., Finch, M., Drucker, S., Tan, D., & Snyder, J. (2012). Foveated 3D graphics. ACM Transactions on Graphics, 31(6), Article 164.

[15] Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? A literature review of empirical studies on gamification. Proceedings of the 47th Hawaii International Conference on System Sciences, 3025-3034.

[16] Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. Journal of Basic Engineering, 82(1), 35-45.

[17] Karis, B. (2021). A deep dive into Nanite virtualized geometry. SIGGRAPH 2021 Advances in Real-Time Rendering Course. Epic Games.

[18] Krishnan, S., Ajikumar, S., Shafi, A., Krishnan, P., & Joseph, A. (2024). Metaverse in agriculture: Transforming future. International Research Journal on Advanced Engineering and Management, 2, 3636-3640.

[19] Lee, L. H., Braud, T., Zhou, P., Wang, L., Xu, D., Lin, Z., et al. (2021). All one needs to know about metaverse: A complete survey on technological singularity, virtual ecosystem, and research agenda. arXiv preprint arXiv:2110.05352.

[20] Lin, B. B., Philpott, S. M., & Jha, S. (2015). The future of urban agriculture and biodiversity-ecosystem services: Challenges and next steps. Basic and Applied Ecology, 16, 189-201.

[21] Marks, S., Windsor, J., & Wunsche, B. (2020). Evaluation of game engines for simulated surgical training. Proceedings of the 5th ACM SIGGRAPH Symposium on Interactive 3D Graphics and Games, 1-8.

[22] Mourtzis, D., Zogopoulos, V., & Vlachou, E. (2020). Augmented reality application to support remote maintenance as a service in the robotics industry. Procedia CIRP, 63, 46-51.

[23] Neethirajan, S., & Kemp, B. (2021). Digital twins in livestock farming. Animals, 11(4), 1008.

[24] Pylianidis, C., Osinga, S., & Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. Computers and Electronics in Agriculture, 184, 105942.

[25] Resh, H. M. (2012). Hydroponic food production: A definitive guidebook for the advanced home gardener and the commercial hydroponic grower (7th ed.). CRC Press.

[26] Saaid, M. F., Yahya, N. H. N., Noor, M. Z. H., & Ali, M. S. A. M. (2015). A development of an automatic microcontroller system for deep water culture (DWC). 2015 IEEE Conference on Systems, Process and Control, 68-73.

[27] Santosh, D. T., & Gaikwad, D. (2023). Advances in hydroponic systems: Types and management.

[28] Sivakumar, P., Prabhakaran, J., Karthikeyan, S., & Saravanan, K. (2020). IoT based automated hydroponics system using deep learning. International Journal of Recent Technology and Engineering, 8(6), 3942-3946.

[29] Taha, M. F., Mao, H., Zhang, Z., Elmasry, G., Awad, M. A., Abdalla, A., Mousa, S., Elwakeel, A. E., & Elsherbiny, O. (2025). Emerging technologies for precision crop management towards Agriculture 5.0: A comprehensive overview. Agriculture, 15, 582.

[30] Thompson, C., Voglmayr, M., Schett, M., & Oulasvirta, A. (2019). Real-time rendering of massive oceanographic datasets in Unreal Engine 4. IEEE VIS Arts Program (VISAP), 1-5.

[31] Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S. (2021). Digital twins in smart farming. Agricultural Systems, 189, 103046.

[32] Wang, Y., Su, Z., Zhang, N., Xing, R., Liu, D., Luan, T. H., & Shen, X. (2022). A survey on metaverse: Fundamentals, security, and privacy. IEEE Communications Surveys & Tutorials, 25(1), 319-352.

[33] Wenzel, E. M., Arruda, M., Kistler, D. J., & Wightman, F. L. (1993). Localization using no individualized head-related transfer functions. Journal of the Acoustical Society of America, 94(1), 111-123.