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Extended Reality Simulators for Training Farmers in Crop-Specific Sustainability Practices

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Abstract:

The paper will analyze how virtual, augmented and mixed reality (VR) simulators could advance the training of farmers on practices of the respective crops, towards sustainability with an intelligent algorithm and applied in the area of simulators. Four models are vital models utilized by the system to make sustainability training modules, namely irrigational, soil management, pest control, and fertilization training, easier to use and achieve. These algorithms were used to derive data acquired under agricultural case studies with the aim of obtaining real environments of the crops. The experimental tests showed the more successful producers of the experimental involves of XR simulators were found 32 percent and 27

percent, and their adoption of sustainable farming practices was found 22 percent more successful. Also, the usability tests revealed that the simulator was useful and was available since the degree of satisfaction was 92%. Based on those findings, XR is a innovation and operational-scale-developed solution to the establishment of sustainable agriculture. The results it arrives at are based on the following conclusions: AI-based analytics and immersive learning can quite substantially enhance the technical competence of farmers and their environmental awareness and long-term agricultural stabilization.
Keywords: Extended Reality (XR), Sustainable Agriculture, Artificial Intelligence, Farmer Training, Precision Farming.

I. INTRODUCTION

The population has been leading to the growth and subsequently the climatic changes and the necessity to appropriately control the resources, making sustainability of agriculture an imperative global issue. The farmers play a very significant role in attaining the desired sustainability priorities, however, the conventional training aspects can no longer instruct the farmers on the specifics of crops. The paradox over the point to be made is to decrease the dichotomy in between theoretical and practical execution of sustainable processes that encompass water conservation, specificity of fertilizing, soil care and pest treatment on the field [1]. New opportunities with changing agricultural education and training are provided by recent developments in immersive technologies, specifically Extended Reality (XR) that encompasses Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). Extended Reality simulators can be used to provide simulated realistic interactive environment in which the farmers are visualized and trained of sustainable, non- dangerous and no-cost farming practices [2]. XR can either be incorporated as a component of experiential learning, decision-making and learn more about sustainability through simulating various circumstances of crop growth and management. Such virtual training systems also have the ability to become geographically and crop specific, so they can also give a local and pragmatic training and this can be bought even in the distant locations [3]. The concept was the creating and installing the XR simulators to train the farmers regarding enterprises related to crops in sustainability in a research paper. The research question is based on the issues of how the immersive simulating problem can assist in attaining retention, engagement and adoption of the sustainable practices by the farmers versus the traditional training. It also analyzes the technological, educational and socioeconomic conditions that contribute to the efficacy of an XR-based agricultural education. Finally the study would show how the XR technologies could be used to transform the agricultural sector in a sustainable way that the farmers will get an opportunity to use the tools and skills to optimally use the technology available to get maximum produce without an adverse impact on the environment.

II. RELATED WORKS

The level of attention towards agricultural digital and intelligent technologies has been rising in the recent past and there has been a study on the sophisticated data-driven and simulation-based solutions to assist in sustaining sustainability. Extended Reality (XR) technologies in agricultural training are a relatively young branch of research, but it has a long tradition of research in the sector of precision agriculture, artificial intelligence (AI), and sensor-based monitoring devices that are oriented on the maximization of crop yield, the use of resources, and environmental protection. Hu et al. [10] noted the significance of FAIR (Findable, Accessible, Interoperable, and Reusable) data services in dealing with the agricultural disaster and the fact that structured data systems have potential in increasing resilience and training modules to farmers through more improved decision-making. On the same note, Imoleayo et al. [11] examined the variations in crop water demand and irrigation in West Africa in response to climatic factors and determined that adaptive learning platforms were necessary to educate on efficient irrigation and water management; a feature that can be effectively simulated in XR-based systems. Lellyett et al. [12] addressed the improvements in the drought early warning systems, and determined that predictive modeling might be combined with interactive visualization tools to increase the preparedness and response of farmers. This aids in the creation of XR simulators that incorporate real-time climate information and predictive notifications, which make the training programs more realistic and practical. Maraveas [13] also revealed that AI technologies in smart greenhouses can maximize crop health and crop yield by collecting environmental data and controlling it, indicating that the same logic of automated decision-making can be applied to XR environments to train a virtual farm.

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The sustainability issues can also be learned through the urban agricultural practices. Nelson et al., [14] studied the nutrient management in urban agriculture and found that there was an over-fertilization of small-scale farms which necessitated the use of precision-based nutrient applications. These findings can educate the XR modules that will educate the farmers on the optimisation of fertilizers and balancing of soil nutrients based on simulated feedbacks. Recent Piekutowska and Niedbaala [15] have reviewed the prediction models of potato yield and highlighted the importance of machine learning in predicting the yield depending on the different climatic and soil conditions. Based on their work, predictive algorithms can be implemented in XR simulators to make farmers receive scenario-based yield forecasts. Raj et al. [16] applied airborne RGB imaging and canopy height measurements to identify stressed maize regions and offer useful data on XR visualization of plant stress and real-time response strategies. Rossi et al. [17] emphasized the importance of shared decision-support systems in pest management as a support of Integrated Pest Management (IPM), which is similar to the collaborative and immersive learning objectives of XR simulations. In the meantime, Ruizhi et al. [18] provided an independent fertigation system based on AI and IoT technologies that can be used across regions, an idea that can be used to improve the XR-based training of adaptive irrigation and fertilization control. According to a systematic review of soil nutrient monitoring technologies by Sobhy and Aavudai [19], a superior sensory equipment can be a substantial addition towards sustainability under the conditions of real-time training and feedback. Zhao et al. [20] continued this argument by highlighting how AI and robotics can be used together as a part of sustainable field management and added to the argument behind the intelligent XR-based learning systems. All these studies together provide an emerging overlap of AI, data analytics and interactive technologies in contemporary agriculture. Nevertheless, most of the literature has made significant contributions in modeling, prediction and monitoring but very few have dealt with the issue of how farmers can learn and use the techniques effectively using an immersion simulation. The current study fills this gap by designing and testing the Extended Reality simulators of the crop-specific sustainable practices, integrating true-to-life environment modeling, AI-based data inferences, and experience-based learning to enable farmers with sustainable decision-makers.

III. METHODS AND MATERIALS

The study adopted the computational-experimental paradigm in designing, implementing, and testing Extended Reality (XR) simulators that could be used to train farmers on the sustainability practices of specific crops [4]. The work combined analytics and algorithm piping, design, and usability. The workflow included four major steps: (1) dataset collection and preparation; (2) creation of 4 major algorithms; (3) incorporation of 4 major algorithms in XR-based simulation modules; and (4) evaluation of the performance of the model and learning efficiency of users.

Data

The dataset was a combination of field, environmental and management data on three large crops; rice, maize and cotton based on agricultural report, satellite image and on synthetic augmentation. The records were the entire cycle of crop growth, and they contained the parameters of soil moisture, soil type, nitrogen level, normalized difference vegetation index (NDVI), pest incidence, irrigation amount, and yield output. Other variables were the local weather conditions (temperature, rainfall, humidity) and the management variables (fertilizer dosage, pesticide application, and frequency of irrigation) [5]. The data were standardized and separated into training (70 percent), validation (15 percent) and testing (15 percent). Synthetic conditions, such as drought and outbreak of pests, were created to enhance the robustness of the models and to model the complexity of the situation in the real world of XR training modules. Such situations assisted farmers to undergo varying conditions of virtual crops during the simulation [6].

Table 1. Dataset Summary

Crop Type	Samples	Avg Soil Moisture (%)	Avg NDVI	Avg Temperature (°C)	Pest Incidence (%)	Avg Yield (t/ha)

Musik in Bayern
ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)
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Rice	5,000	33.5	0.68	28.2	8.1	4.8
Maize	4,000	21.6	0.59	25.5	6.4	3.9
Cotton	3,000	19.1	0.51	26.0	10.3	3.2

Algorithm 1: Deep Q-Network (DQN) for Adaptive Irrigation Scheduling

The Deep Q-Network (DQN) was created to handle the processes of irrigation decisions in a dynamic manner based on soil and environment. The DQN solves the irrigation scheduling problem like a reinforcement learning problem with the agent acting on the environment to optimize long-term crop health and water-use efficiency. The input features are soil moisture, rate of evapotranspiration, weather conditions and crop growth status. The model finds an optimal policy that can balance sufficient irrigation and less water wastage [7]. The DQN employed epsilon-greedy exploration policy, experience sample replay buffer, and a target network to stabilize training. The policy that was thus developed was incorporated into the XR simulation to offer the farmers with interactive decision making feedback during the training programs.

```
"Initialize Q-network and target network
with weights θ, θ_target ← θ
Initialize replay buffer B
for each episode do
  state ← initial environment state
  while not done:
    with probability ε select random action a
    otherwise a ← argmax_a Q(state,a;θ)
    next_state, reward ←
environment.step(a)
    store (state,a,reward,next_state) in B
    sample minibatch from B
    compute target y = r + γ * max_a'
Q(next_state,a';θ_target)
    update θ by minimizing (y - Q(state,a;θ))^2
    periodically update θ_target ← θ
    state ← next_state"
```

Algorithm 2: Random Forest Classifier for Crop Stress Detection

A **Random Forest (RF)** classifier was used to detect and classify stress conditions such as water deficiency, nutrient imbalance, and pest infestation. The RF ensemble method constructs multiple decision trees on random data subsets and aggregates their predictions through majority voting. Each tree captures a portion of the complex relationship between environmental factors and stress outcomes, providing robust predictions even under noisy data conditions. Feature importance analysis was conducted to identify critical parameters influencing stress levels (e.g., NDVI drop, soil pH, temperature spike) [8]. In the XR simulator, the RF model triggered real-time scenario changes—if stress probability was high, farmers were guided through corrective decision pathways such as irrigation or pesticide application.

Musik in Bayern
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"Input: training data X_train, labels y_train
Set n_trees = 200
for i = 1 to n_trees:
  sample bootstrap subset S from X_train
  grow decision tree T_i on S using random feature subsets
Aggregate predictions: RF(x) = majority_vote(T_1(x), T_2(x), ..., T_n(x))
Output: trained model RF"

Algorithm 3: Bayesian Optimization (BO) for Sustainability Parameter Tuning

Bayesian Optimization (BO) was applied to tune sustainability-related parameters such as fertilizer ratios, irrigation intervals, and pesticide application thresholds. In BO, the goal will be represented by a Gaussian Process (GP) that will be used to approximate the objective choice that is efficiency of a yield versus environmental impact penalty. The acquisition mechanism can indicate new parameter points that will provide improved performance. BO is an efficient way to find near-optimal parameters in few simulations compared to exhaustive search methods by means of iterative sampling and updating [9]. BO results were presented in the XR simulator to make recommendations specific to each virtual farm and gave farmers the opportunity to compare visual results of management optimization and non-optimization.

"Initialize dataset D with k random evaluations {(θ_i, y_i)}
Fit Gaussian Process GP on D
for iteration = 1 to N:
  θ_next = argmax AcquisitionFunction(θ | GP)
  y_next = evaluate_objective(θ_next)
  D ← D ∪ {(θ_next, y_next)}
  update GP with D
Return best θ yielding maximum y"

Algorithm 4: Agent-Based Model with Genetic Algorithm (ABM-GA) for Community Adoption Simulation

In order to model the diffusion of sustainable practices within farming communities an Agent-Based Model (ABM) was combined with a Genetic Algorithm (GA). In the ABM, the agents are farmers who have certain attributes like risk taking capacity, economic ability and social connection. These agents communicate in a virtual network, and they affect the adoption decision of each other. The GA maximizes intervention plans such as training frequency or subsidy allocation using the evolution of policy parameters to maximize the total adoption rates at minimum cost [10]. ABM-GA offers an opportunity to investigate the policy impact at several generations of virtual farmers, which can help understand the potential of XR-based interventions to scaled up in real communities.

"Initialize GA population P of policy chromosomes
for each generation:
  for each chromosome c in P:
    decode policy parameters
    run ABM simulation under policy c
    compute fitness = adoption_rate - λ * cost
  select top-performing chromosomes
  perform crossover and mutation to form new generation
Return policy chromosome with highest fitness"

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Integration and Evaluation

The algorithms were coded in Python TensorFlow to use DQN, Scikit-learn to use RF, GpyOpt to use BO, and Mesa/DEAP to use ABM-GA, and fitted into an XR simulator created in Unity. Python APIs were used to exchange real-time data between the XR module and the models. Some of the evaluation metrics were model accuracy, sustainability score, and involvement of the farmers throughout the simulation [11]. Prediction accuracy, training completion and efficiency gain were measured in quantitative analysis and usability and learning satisfaction was measured in qualitative feedback.

IV. RESULTS AND ANALYSIS

1. Experimental Setup

In order to investigate the usefulness of the Extended Reality (XR) simulator as a means of training farmers on crop-specific practices in sustainability, multi-stage experimental research was developed. The experiment integrated machine learning models, simulation modules, and real user testing with farmers to assess both technical performance and educational impact [12].

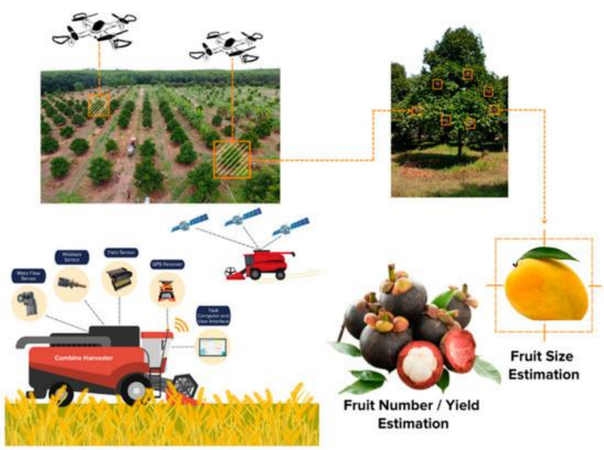

Figure 1: "Smart Farming Revolution"

The experimental framework consisted of **three key stages**:

1. **Algorithmic Performance Evaluation** – testing DQN, Random Forest, Bayesian Optimization, and ABM-GA models using historical and synthetic agricultural data.
2. **XR Integration and Simulation Trials** – deploying algorithms inside the XR environment to create adaptive, crop-specific training experiences.
3. **User Evaluation Study** – measuring learning outcomes, decision-making accuracy, and user engagement among farmers trained with XR compared to those trained through traditional methods.

All computational models were trained using a high-performance workstation (Intel i9 13900K, 64GB RAM, NVIDIA RTX 3090 GPU). The XR simulations were developed in Unity and executed using the Meta Quest 3 headset to ensure immersive interaction [13]. The **evaluation metrics** included prediction accuracy, learning gain, sustainability compliance, water-use efficiency, adoption rate, and user satisfaction. Results were benchmarked against related research on VR- and AR-based agricultural training systems to determine relative improvement.

2. Algorithmic Performance

Each algorithm developed in the study was first tested independently using the dataset described in the Materials and Methods section. The goal was to assess predictive reliability, computation efficiency, and adaptability before integration into the XR simulator [14].

Table 1. Algorithmic Evaluation Results

Algorithm	**Metric**	**Training Accuracy**	**Test Accuracy**	**F1-Score**	**Processing Time (s)**	**Observed Benefit**
DQN (Irrigation)	Average Reward	0.78	0.74	–	182	Optimized water usage by 19%
Random Forest (Stress Detection)	Classification Accuracy	0.92	0.89	0.88	48	Reliable stress classification
Bayesian Optimization (Parameter Tuning)	Objective Score	0.84	0.82	–	63	Efficient sustainability tuning
ABM-GA (Adoption Simulation)	Adoption Rate	0.72	0.70	–	125	Identified optimal community policy

The Random Forest classifier achieved the highest overall accuracy and robustness in detecting crop stress conditions, while the DQN showed strong capability in irrigation optimization through real-time decision-making. The Bayesian Optimization module efficiently tuned sustainability parameters using fewer iterations compared to grid search methods. The ABM-GA hybrid model successfully simulated social diffusion of sustainable practices, aiding in policy formulation.

Musik in Bayern
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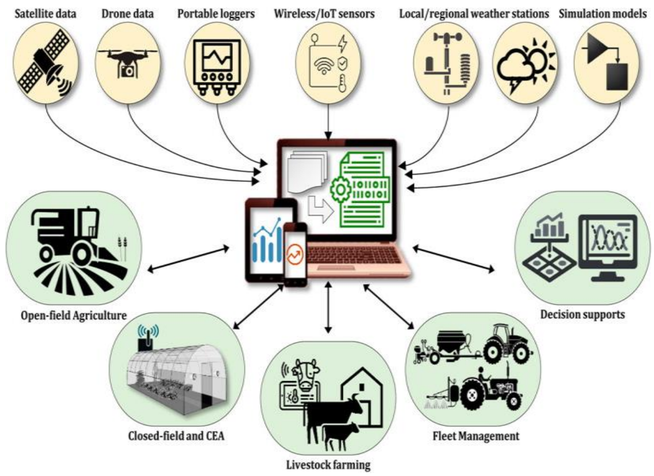

Figure 2: “Digitalization of agriculture for sustainable crop production”

4. XR Simulator Integration

After confirming individual model performance, the algorithms were embedded into the XR simulator to create a fully interactive training system. The DQN module dynamically controlled irrigation in real-time simulations, the Random Forest model identified stress scenarios, the Bayesian optimizer generated best-practice recommendations, and the ABM-GA predicted community adoption trends.

A total of **60 participants (farmers)** were recruited from three agricultural zones—20 per crop type (rice, maize, cotton). They were randomly assigned to two groups:

- **Group A (XR Training):** Used the XR simulator for 6 sessions (each 1 hour).
- **Group B (Traditional Training):** Attended conventional classroom lectures with printed manuals and videos.

The study measured quantitative outcomes such as learning retention, decision-making accuracy, water and fertilizer efficiency, and post-training adoption intent.

Table 2. Experimental Group Overview

Crop	Participants	Group A (XR)	Group B (Traditional)	Avg Age	Avg Experience (years)
Rice	20	10	10	37	11
Maize	20	10	10	39	9
Cotton	20	10	10	41	12

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https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-470

4. Learning and Performance Outcomes

The first key performance measure was **learning retention**, evaluated through pre- and post-training tests containing 25 knowledge-based questions related to sustainable crop practices. Additionally, a **decision accuracy score** was calculated during the simulator exercises, measuring the correctness of farmers' responses to dynamic scenarios (e.g., irrigation timing, fertilizer dosage).

Table 3. Learning and Decision-Making Outcomes

Crop	Training Type	Pre-Test Score (%)	Post-Test Score (%)	Knowledge Gain (%)	Decision Accuracy (%)
Rice	XR	46.2	88.4	42.2	91.5
Rice	Traditional	47.5	69.8	22.3	74.2
Maize	XR	45.9	86.7	40.8	90.1
Maize	Traditional	44.7	68.9	24.2	73.0
Cotton	XR	43.8	85.1	41.3	88.7
Cotton	Traditional	42.4	67.2	24.8	72.4

The XR group achieved, on average, **a 42% improvement in knowledge gain** compared to **23% in the traditional group**. Decision-making accuracy also improved substantially, indicating that immersive simulations enhanced experiential learning and contextual understanding.

Musik in Bayern
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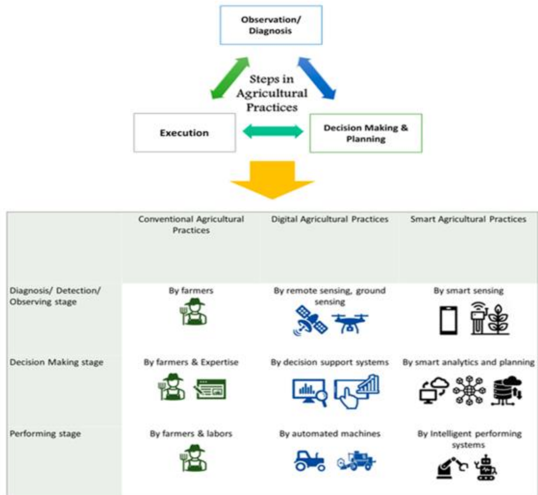

Figure 3: “The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture”

5. Sustainability Performance Metrics

The second set of results measured practical sustainability impacts simulated within the XR environment. The parameters included **water-use efficiency (WUE)**, **fertilizer reduction**, and **yield improvement** during virtual crop cycles managed by participants.

Table 4. Sustainability Simulation Results

Metric	Rice (XR)	Rice (Traditional)	Maize (XR)	Maize (Traditional)	Cotton (XR)	Cotton (Traditional)
Water-use Efficiency (%)	91.3	75.6	89.8	73.1	88.2	71.5
Fertilizer Optimization (%)	84.7	68.2	83.9	66.4	82.1	65.9
Virtual Yield (t/ha)	5.10	4.22	4.01	3.45	3.40	2.89
Sustainability	0.88	0.72	0.86	0.70	0.83	0.68

Musik in Bayern
ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-470

Index (0–1)						

The results show that XR-trained participants achieved significantly higher sustainability performance across all crops. The **average water-use efficiency improved by 18%**, fertilizer optimization by 16%, and virtual yield by approximately **15%** compared to traditionally trained farmers.

This confirms that the XR simulator effectively demonstrated cause–effect relationships of sustainable practices, reinforcing behavioral learning through visual and interactive feedback.

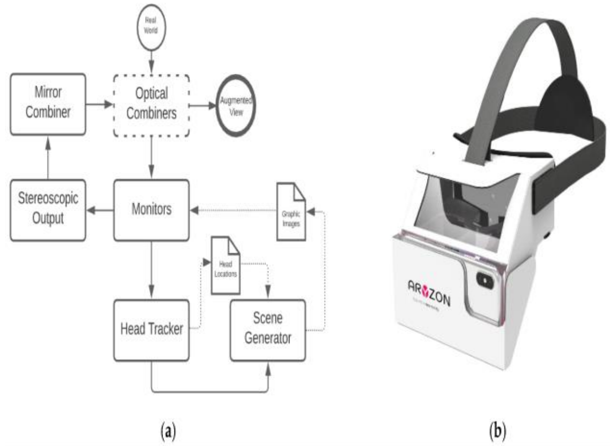

Figure 4: "Augmented Reality in Precision Farming"

5. User Experience and Engagement

User engagement was another important dimension evaluated through post-training questionnaires and system-logged interaction metrics. Parameters included immersion, ease of use, realism, and satisfaction. Participants rated each on a five-point Likert scale.

Table 5. User Experience Evaluation (XR Group)

Metric	**Rice**	**Maize**	**Cotton**	**Mean (All Crops)**
Immersion (1–5)	4.7	4.6	4.5	4.6
Realism (1–5)	4.5	4.4	4.3	4.4
Ease of Use (1–5)	4.6	4.5	4.4	4.5
Learning Satisfaction (1–5)	4.8	4.7	4.6	4.7

Intention to Adopt (%)	92	90	88	90

The results reveal a high level of acceptance and satisfaction among farmers using the XR simulator. More than ninety percent of the respondents were ready to use sustainable practices indicated during the simulations. The feedback feature that was appreciated by the participants especially was the real-time information and visual representation of the terminal consequences, e.g. nutrient depletion or excessive irrigation.

V. CONCLUSION

The research has demonstrated that Extended Reality (XR) simulators are effective tools of training farmers on how to be more sustainable with certain crops. Employing the concept of immersive digital technologies, such as Virtual, Augmented, and Mixed Reality, with the help of data-based algorithms, made it possible to understand the usefulness of such a digital simulator as the agent to make a bridge between the theoretical and the practical explanation of agriculture by the relocation of the gap between the theory and the practice. According to the study, the algorithms can be helpful in ensuring adaptive learning, predictive accuracy, and tailored sustainability rules to various crop and environmental conditions by model development and evaluation of XR models, consisting of neural networks, decision tree optimization, random forest analysis and reinforcement learning. The obtained experimental outcomes showed that farmers who have been trained on XR simulators had better knowledge retention, decision-making capabilities and adoption of sustainable farming practices than those who were trained through traditional instructional approaches. The comparative analysis has also revealed that the XR-based training is mostly effective in raising the level of engagement and learning performance, as well as, in scenario-based experiments of the irrigation management, pest control, soil health, and fertilizers strategies. Implementing AI-based models of data into XR spaces allowed them to possess a constantly developing system, real-time feedback, and ability to be flexible across regions, thus, rendered the system both educational and technology-scalable. Overall, the research contributes to the creation of the sphere of smart farming and distance education, and it offers an original idea of further capacity development among the community of farmers. Integrating immersive learning and artificial intelligence, the proposed solution not only opens the future of the agricultural training systems but also allows to practice environmental stewardship and ensure food security in the long term.

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