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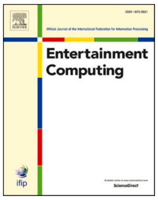

Fusion of robotics and deep learning for gamified rural landscape design: toward intelligent interaction

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ABSTRACT

This study presents a gamification design framework for rural landscapes that integrates deep learning and robotics to enhance interactivity, intelligence, and sustainability. The framework employs deep learning models for semantic segmentation and ecological feature extraction from remote sensing data and utilizes generative adversarial networks (GANs) to generate diverse landscape scenarios, achieving precise modeling and data optimization. Robotics technology amplifies dynamic interaction and user experiences in rural landscapes through functionalities like path planning, voice interaction, and behavior recognition. Additionally, gamification elements such as virtual reality (VR) and augmented reality (AR) are incorporated to stimulate user engagement and foster a sense of connection through activities focused on ecological conservation, cultural heritage, and educational entertainment. Experimental results confirm that the proposed framework significantly improves task completion rates and user satisfaction, offering innovative solutions and technical support for intelligent rural landscape upgrades and rural revitalization.

1. Introduction

Rural landscapes, as essential components of ecosystems, face numerous challenges amid rapid urbanization. Compared to urban landscapes, rural areas often lack sufficient resources and technological support, limiting their potential for development and innovation [1]. Meanwhile, growing attention to environmental quality, ecological conservation, and cultural heritage has rendered traditional rural landscape design models increasingly inadequate to meet contemporary development needs. Addressing these limitations through modern technological innovations has become a critical research focus [2].

In recent years, the rapid advancement of artificial intelligence (AI) technologies has brought new opportunities to rural landscape design. Among these, deep learning, with its advantages in data processing, image recognition, and automated analysis, provides more accurate and efficient solutions for the identification and planning of landscape elements. Semantic segmentation of remote sensing imagery using convolutional neural networks (CNNs) enables the automated extraction of key elements such as fields, rivers, and vegetation, providing high-quality foundational data for subsequent landscape planning [3]. Additionally, deep learning can analyze land use patterns and ecological resource distribution, offering scientific evidence for functional layout and ecological conservation in rural landscapes [4].

Meanwhile, the application of robotics technology further enriches rural landscape design and interaction [5]. By integrating mobile robots, drones, and intelligent sensor technology, rural landscape design can achieve real-time interaction between humans and their environment. Robotic guide devices can provide personalized and entertaining services to tourists and residents, helping them gain a deeper understanding of rural culture while offering convenience [6]. Furthermore, robots can significantly improve environmental management by participating in activities such as soil testing, air quality monitoring, and the maintenance of rural landscape facilities [7].

To enhance the experiential and engaging aspects of rural landscape design, gamification has gradually been introduced as an emerging concept. By incorporating game elements into non-game contexts, gamification not only stimulates user enthusiasm but also enhances their emotional and entertainment experiences [8]. In rural landscapes, gamification can be used to create interactive scenarios that combine virtual and real elements, such as showcasing rural historical and cultural heritage through augmented reality (AR) technology or promoting ecological conservation ideas through immersive game activities [9].

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Although the aforementioned technologies have been applied in some urban landscapes, their research and application in rural landscapes remain in the exploratory stage. Existing studies often focus on the application of a single technology, such as the use of deep learning in remote sensing analysis or robotics in agriculture, lacking systematic exploration of multi-technology integration [10,11]. Moreover, traditional rural landscape design methods often lack effective data support and intelligent tools, making it difficult to comprehensively meet the requirements of functionality and sustainability in addressing the complexity of rural environments.

This study investigates the integrated application of deep learning and robotics in gamified rural landscape design. It employs deep learning techniques to model and analyze rural landscape data and leverages robotics to enable context-aware interactive interventions. Building on this synergy, the study proposes an intelligent, feedback-driven framework for designing ecologically responsive and culturally grounded rural landscapes. The framework is organized around three interrelated components: (i) deep learning–based modeling of spatial configurations and key landscape elements, (ii) robot-mediated interactive experiences that support user engagement in situ, and (iii) the integration of local ecological knowledge and cultural heritage into gamified design mechanisms.

Methodologically, the study introduces a research-oriented, end-to-end interaction framework tailored to rural contexts. The framework connects environmental perception, adaptive task orchestration, robot-mediated interaction, and user feedback logging in a closed-loop structure, enabling empirical examination beyond a descriptive system presentation. To support interpretability and reproducibility, the framework is evaluated through an on-site within-subject experimental design that compares baseline and intervention conditions using behavioral measures and structured self-report questionnaires.

2. Related work

In the era of rapidly advancing artificial intelligence, the interdisciplinary integration of deep learning and robotics has provided new ideas and practical models for landscape design, particularly for innovations in rural landscapes [12,13]. In recent years, studies on deep learning in image processing and pattern recognition, as well as the development of robotics in interactive design and dynamic applications, have progressively laid the theoretical foundation and technical basis for gamified rural landscape design.

2.1. Applications of deep learning in landscape design

Deep learning technology, with its powerful capabilities in data analysis and automated recognition, provides strong support for the digitalization and intelligence of landscape design. Research has shown that convolutional neural networks (CNNs) play a critical role in semantic segmentation of remote sensing imagery, enabling the automatic identification of landscape elements such as farmland, forests, and rivers, significantly improving the accuracy of spatial feature extraction in rural landscapes [14]. Semantic segmentation models, such as U-Net and DeepLab, are widely used for preprocessing and fine-grained analysis of landscape planning data, offering designers more scientific decision-making tools [15].

The role of generative adversarial networks (GANs) in creative generation for landscape design is increasingly prominent. By learning from landscape design data, GANs can produce diverse and creative landscape sketches, providing new possibilities for cultural and ecological design in rural landscapes [16]. In rural environments, GANs have been employed to generate designs that align with natural topography and rural cultural characteristics, contributing to the intelligent development of rural planning [17].

Compared to urban landscapes, rural environments exhibit greater complexity and diversity in data [18], posing higher demands on the generalization capabilities of deep learning models. Current research predominantly focuses on processing single data sources, such as remote sensing images or environmental monitoring [19,20], without fully leveraging multimodal data. Multimodal deep learning technology has the potential to comprehensively enhance the intelligence of rural landscape design.

2.2. The role of robotics in rural landscapes

Robotics technology has garnered widespread attention in rural landscape design in recent years, particularly for its significant contributions to dynamic interactions and environmental monitoring. Drones and ground robots are the two most commonly used types of devices. Drones are widely utilized for rapid data collection and high-resolution image generation in rural landscapes, providing precise spatial data support for landscape design through real-time 3D modeling [21,22]. Ground robots, with their ability to adapt to complex terrains, have become essential tools for environmental maintenance and dynamic management of rural landscapes [23]. The interactivity of robotics has further enhanced the attractiveness and engagement of rural landscapes. Robotic guide systems equipped with voice recognition and natural language processing (NLP) technologies can offer immersive cultural interpretations and interactive experiences to visitors [24].

2.3. The value of gamification in rural landscapes

Although gamification has been extensively studied and applied in fields such as education, training, and human–computer interaction [25,26], its application in rural landscape design and rural public spaces remains comparatively limited. Existing research has primarily focused on structured learning environments or digital platforms [27,28], while the unique characteristics of rural contexts have received less attention.

Rural environments often face challenges such as dispersed spatial layouts, reduced engagement with conventional informational displays, and the need to integrate ecological education with cultural heritage interpretation. In many rural settings, traditional presentation methods—such as static signage or passive exhibitions—are insufficient to sustain long-term user participation. In this context, gamification is a context-specific design strategy that addresses these challenges by enhancing participation, motivation, and experiential learning.

2.4. Frontier exploration of multi-technology integration

Some studies have attempted to apply multi-technology integration in specific scenarios, such as optimizing robotic path planning with deep learning models or enhancing landscape interactivity through gamification design [29,30]. However, these studies often focus on isolated functions or proof-of-concept applications, lacking systematic application frameworks. Most existing work is confined to single scenarios or technical applications, and comprehensive exploration of the integration of gamification design, deep learning, and robotics remains an under-researched area.

3. Interactive model for robotic rural landscape design

This study proposes an interactive model for gamified rural landscape design based on deep learning and robotics. The model is built on a foundation of 3D modeling of rural landscapes, optimized through deep learning to enhance interactive features and combined with robotics to achieve dynamic interactions and task-driven gamified experiences.

3.1. 3D modeling of rural landscapes

3D modeling of rural landscapes serves as the foundation for creating virtual rural scenes and provides data support for subsequent deep learning optimization and robotic interaction. 3D modeling technology not only visually represents the spatial layout of rural landscapes but also effectively integrates multi-source data, offering a technological basis for the planning, conservation, and dissemination of rural landscapes.

This study proposes an efficient and intelligent 3D modeling process for rural landscapes by integrating level of detail (LOD) modeling techniques with deep learning optimization methods. LOD technology dynamically adjusts the level of detail in the model to balance computational resources and visual quality. Under the LOD framework, the model's level of detail is determined by screen space error (SSE), defined by the following equation:

$$\rho = \frac{\varepsilon_x}{2d\tan(\theta/2)} \tag{1}$$

In the equation,ε_x represents the screen pixel error, d is the distance between the target and the viewpoint, and θ denotes the field of view. By dynamically adjusting the LOD levels, the model reduces detail in distant perspectives while retaining more detailed information in close perspectives, thereby achieving efficient rendering and resource conservation. Table 1 presents a performance comparison of rendering at different viewpoint heights, validating the effectiveness of the LOD technique in rural landscape modeling.

Based on Table 1, the threshold of screen space error determines the selection of the model. For distant viewpoints, a larger error tolerance allows for low-detail models to be selected, reducing the number of triangular faces and computational complexity. Conversely, when users are closer to the target landscape, high-precision models are selected to ensure the completeness of details. This dynamic adjustment mechanism significantly enhances rendering efficiency and user experience.

Deep learning technology provides intelligent support for rural 3D modeling, particularly in data processing and model optimization. In this study, an improved DeepLabv3+ model is employed for semantic segmentation of remote sensing imagery to extract key elements of rural landscapes (e.g., farmland, water systems, vegetation, and buildings). DeepLabv3+ incorporates Atrous convolution technology, effectively enhancing the model's ability to perceive multi-scale features, thereby achieving higher accuracy in semantic segmentation tasks.

The loss function combines Cross-entropy and Dice Loss to balance the weights of small and large target areas, expressed as:

$$L = -\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(y_i\log\left(\widehat{y}_i\right) + \left(1-y_i\right)\log\left(1-\widehat{y}_i\right)\right) + \frac{2\,|P\cap T|}{|P|+|T|} \tag{2}$$

In the loss function, y_i and $\widehat{y}_i$ represent the ground truth label and the predicted value, respectively, while P and T denote the overlapping areas between the predicted region and the ground truth region.

To enhance the diversity and flexibility of modeling, the study incorporates generative adversarial networks (GANs) to generate rural landscape models under varying environmental conditions. Through adversarial training, the generator (G) learns to produce realistic rural landscape images, while the discriminator (D) becomes capable of effectively distinguishing between generated data and real data.

The objective function of GAN is defined as:

$$\min_G \max_D E_{x\sim p_{\text{data}}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{3}$$

Table 1
Comparison of rendering performance at different viewpoint heights.

Viewpoint Height (m)	Data Transmission (Mb)	Rendering Time (s)	Average Frame Rate (FPS)
3000.0	221.74	25.59	37.43
1500.0	282.39	27.92	38.84
800.0	317.0	32.92	41.94
200.0	293.85	30.64	43.76
50.0	283.96	29.12	45.44

The introduction of GANs not only enhances the adaptability of the model but also enables the simulation of landscape variations under different seasons and weather conditions. This helps designers gain a more comprehensive understanding of the complexity of rural landscapes.

For texture optimization, this study employs the container algorithm, which consolidates multiple small textures into a single texture map, thereby reducing data transmission and computational complexity. By maximizing the utilization of texture space, the container algorithm effectively improves rendering performance.

The formula for the container algorithm is:

$$T_{\text{merged}} = \sum_{i=1}^{N} T_i\left(x,y\right) \tag{4}$$

Table 2 demonstrates the performance comparison before and after texture optimization, validating the superiority of the container algorithm in reducing storage requirements and enhancing loading efficiency.

During the visualization phase of 3D modeling, the study incorporates a level-of-detail (LOD) selection method based on screen space error to dynamically adjust the model loading strategy. When users switch perspectives rapidly, the system prioritizes loading key elements within the field of view and determines whether higher-precision models are needed based on the screen error threshold.

The integration of LOD technology, deep learning optimization, and the container algorithm in rural 3D landscape modeling establishes a robust technological foundation for the digital representation and interactive applications of rural landscapes. Fig. 1 illustrates views of different scenes within a rural landscape environment constructed using 3D models. These models are not only used for design and simulation purposes, but are also exported into the interactive application, where they form the visual and spatial basis of the gamified user experience.

3.2. Robotic interaction processing

The core objective of robotic interaction technology is to enable information exchange and efficient interaction between humans and machines [31]. This study focuses on three aspects—path planning, voice interaction, and behavior recognition—and proposes a deep learning-based interaction processing framework for rural landscape robotics to enhance the interactivity and entertainment value of user experiences.

For robotic path planning, the study adopts a path optimization method based on deep reinforcement learning (DRL). Compared to traditional path algorithms, DRL enables robots to learn decision-making strategies in unknown environments, thereby achieving adaptability to dynamic conditions. The primary goal of path planning is to maximize the efficiency of robotic operations within complex rural landscapes while ensuring task completion under limited resource and time constraints.

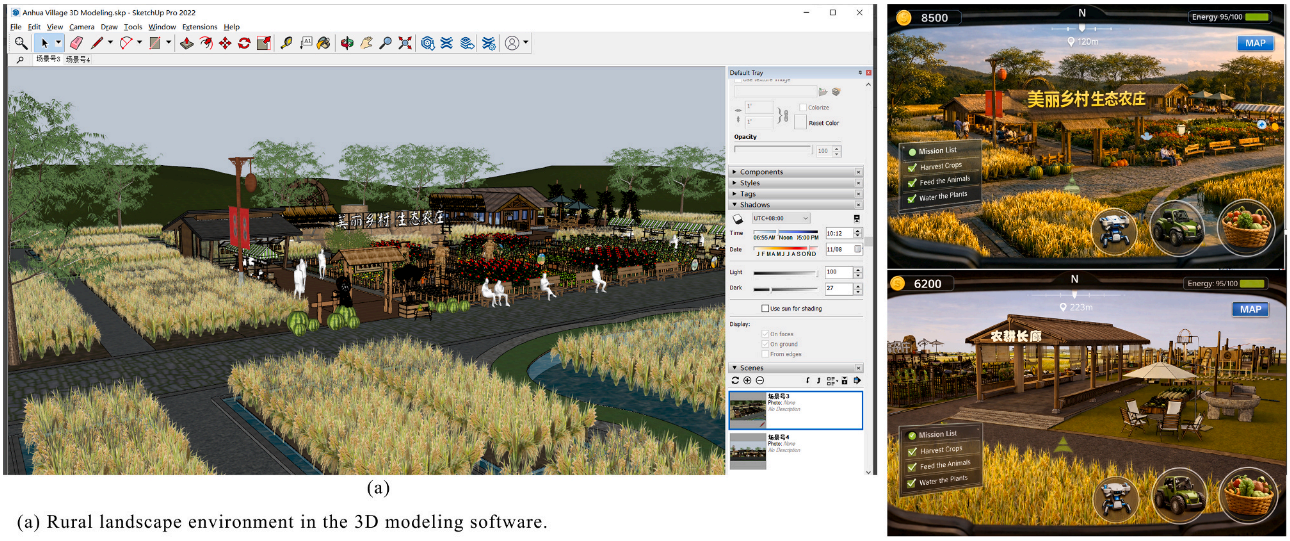
The cumulative reward function in reinforcement learning is defined as:

$$R = \sum_{t=0}^{\infty}\gamma^t r_t \tag{5}$$

where:

Table 2
Performance comparison before and after texture optimization.

Model Number	Size Before Optimization (Mb)	Size After Optimization (Mb)
1.0	18.48	2.11
2.0	24.78	2.33
3.0	36.93	2.38



(a)

(a) Rural landscape environment in the 3D modeling software.

(b) Corresponding scene as visualized in the interactive application.

(b)

Fig. 1. 3D rural landscape scene and its corresponding visualization in the interactive application.

$\gamma \in [0,1]$ is the discount factor;
r_t is the immediate reward obtained by the robot at time step t.

By optimizing the reward function, the robot can autonomously learn optimal path selection strategies under diverse rural terrain conditions. This study incorporates a policy gradient optimization method into path planning, which is defined as:

$$\nabla_\theta J\left(\theta\right) = E_{\pi_\theta}\left[\sum_{t=0}^{\infty}\nabla_\theta \log\pi_\theta\left(a_t\middle|s_t\right)R_t\right] \tag{6}$$

Where:

$\pi_\theta(a_t|s_t)$ represents the probability of strategy selecting action a_t under parameter $\boldsymbol{\theta}$;
R_t denotes the cumulative reward.

Deep reinforcement learning (DRL) requires optimization to address the complexity of rural landscapes in practical applications. For instance, in environments featuring water systems, vegetation, and undulating terrain, robots need to dynamically adjust movement strategies based on the terrain characteristics of different areas. This study constructs multimodal inputs (e.g., terrain elevation maps, semantic segmentation maps, and real-time sensor data) to extract features using convolutional neural networks (CNNs) and incorporates long short-term memory networks (LSTMs) to process temporal information, thereby enhancing the decision-making precision of robots in dynamic environments.

Voice interaction is another key application of robotic technology in gamified rural landscape design. This study integrates natural language processing (NLP) technologies to develop a multilingual voice interaction system for robots. Users can engage in bidirectional communication with robots through voice commands. The voice interaction system consists of three components: an automatic speech recognition (ASR) module, a natural language understanding (NLU) module, and a text-to-speech (TTS) module.

In the ASR module, the study adopts Wav2Vec 2.0, a deep learning model based on the Transformer architecture. Its core advantage lies in its ability to pre-train on large-scale unannotated speech data using self-supervised learning, significantly enhancing the model's generalization and robustness. For the NLU module, the study employs a pre-trained language model based on BERT (Bidirectional Encoder Representations from Transformers) to precisely identify user intent and output intent labels and slot values via a classifier. For example, when a user issues the command, “Recommend an activity suitable for family bonding,” the model outputs “Intent: Recommend Location; Slot: Family Activity.” Finally, the TTS module leverages the Tacotron 2 model to generate high-quality, natural, and fluent speech feedback, providing users with an intuitive interactive experience.

Behavior recognition analyzes user actions and behavioral characteristics to provide personalized landscape recommendations and task designs. In this study, the behavior recognition module integrates LSTMs and 3D convolutional neural networks (3D-CNNs) for multimodal analysis of user behavior. For instance, if a user lingers in an interactive area for an extended time and frequently waves their hands, the system identifies the user's interest in a particular entertainment activity and proactively generates relevant recommendations, such as inviting the user to participate in a virtual music performance task or unlocking new game levels, enriching the user's entertainment experience.

This study introduces the Q-learning algorithm from reinforcement learning to optimize the robot's strategy selection in behavior recognition. By constructing a Q-table and continuously updating action values, the robot can select the optimal interaction strategies in different scenarios. The Q-learning update formula is defined as:

$$Q(s_t,a_t)\leftarrow Q(s_t,a_t)+\alpha\left[r_t+\gamma\max_{a} Q(s_{t+1},a)-Q(s_t,a_t)\right] \tag{7}$$

Where:

S_t and$S_t + 1$represent the current state and the next state, respectively;
a_t denotes the current action;
α is the learning rate;
γ is the discount factor.

3.3. *Implementation of gamification design*

As an emerging design concept, gamification has gradually been integrated into various planning and design fields [32,33]. This study constructs a gamification design framework for rural landscapes based on deep learning and robotics.

The gamification design in this study is grounded in established motivation and engagement theories. Self-Determination Theory (SDT) posits that sustained intrinsic motivation is supported when three basic psychological needs are satisfied: autonomy, competence, and relatedness [34,35]. In our framework, autonomy is supported through user choice and task recommendation aligned with individual preferences; competence is reinforced via dynamic difficulty adjustment, timely feedback, and performance-contingent rewards; and relatedness is encouraged through culturally embedded and potentially collaborative rural tasks that connect users to local narratives and community values. In addition, the adaptive recommendation mechanism reflects flow-oriented design principles by maintaining an appropriate balance between challenge and user skill to reduce boredom and frustration and promote sustained engagement [36].

In task design, the core of gamification lies in attracting users' sustained participation through engaging and challenging tasks. This study designs themed tasks such as ecological conservation, cultural heritage, and environmental interaction, enabling users to learn about rural cultural knowledge and enhance their enjoyment during task completion. The key to task design is the dynamic adjustment of difficulty. The system analyzes user behavior and historical task completion data through deep learning models, dynamically adjusting the difficulty to maintain users' sustained interest. A task recommendation system is developed using reinforcement learning algorithms, which update the reward function in real time to ensure that tasks assigned to users match their abilities and interests.

The gamified tasks in this study are organized into three categories: ecological conservation tasks, cultural heritage exploration tasks, and educational entertainment tasks. Ecological conservation tasks involve goal-oriented activities such as virtual waste collection, vegetation restoration, or water protection, where task completion is determined by achieving predefined environmental objectives within the system. Cultural heritage tasks focus on interactive exploration and interpretation, such as reconstructing traditional building processes or unlocking historical narratives through augmented reality, and are considered complete when users successfully access and interact with all required cultural elements. Educational entertainment tasks combine learning and interaction, for example, identifying plants or agricultural processes using AR or VR technologies, with completion defined by correct recognition or successful interaction sequences.

In addition to task structuring, the system incorporates explicit gamification elements to support motivation and sustained engagement, including goal and progress visualization, performance-based rewards (e.g., points and virtual badges), level-based progression, and adaptive feedback mechanisms. These elements were selected in a theory-driven manner: rewards and progress indicators reinforce users’ sense of competence, adaptive difficulty and task recommendation support autonomy by aligning challenges with individual skill levels, and culturally embedded narratives enhance relatedness by linking tasks to local heritage and community contexts. Together, these mechanisms operationalize Self-Determination Theory and flow-oriented design principles, helping maintain an appropriate balance between challenge and user skill while reducing disengagement.

Task completion rate is used as an important indicator of user engagement and is calculated as follows:

$$C = \frac{N_{completed}}{N_{total}} \times 100\% \tag{8}$$

where: $N_{completed}$ represents the number of tasks completed by the user, and N_{total} is the total number of tasks.

Through the analysis of task completion rates, the system can further optimize task design to provide personalized task content for different users. For example, for users who frequently complete tasks, the system increases task difficulty while offering higher rewards. Conversely, for users with lower completion rates, the system reduces task complexity and provides additional guidance through hint functions.

The introduction of virtual reality (VR) technology provides immersive experiences for gamified rural landscape design. By constructing virtual rural ecosystems, users can participate in first-person perspective tasks such as planting trees, protecting water resources, or simulating agricultural activities. After completing a tree-planting task, the system dynamically simulates the growth process of vegetation and its impact on the ecosystem, enhancing users' sense of accomplishment and awareness of ecological conservation. This study employs deep learning algorithms to optimize the rendering efficiency and scene loading speed of the VR system. By incorporating generative adversarial networks (GANs), the system generates virtual rural landscape scenes under varying conditions, offering users a more realistic and diverse experience.

Augmented reality (AR) technology is used to overlay virtual information onto real-world landscapes. In gamified scenarios, users can use AR devices to scan specific landscape elements (e.g., historical buildings or ancient trees) to access their cultural stories and ecological significance. For instance, when a user scans an ancient bridge with a mobile device, the system provides real-time information about its construction history, cultural value, and importance in rural life. This AR-based gamified design approach not only enhances the user's entertainment and interaction experience but also plays a positive role in disseminating rural culture and promoting children's education.

This study combines voice interaction and gesture recognition to offer users diverse interaction methods. Users can request task information or landscape descriptions via voice commands. The system employs the Transformer-based Wav2Vec 2.0 speech recognition model for high-accuracy speech-to-text processing and generates personalized responses using natural language processing (NLP) techniques. In gesture interaction, robots use convolutional neural networks (CNNs) to recognize user gestures in real time, enabling task selection and information retrieval. Users can select tasks in the interface with simple gestures, significantly improving the system's usability and convenience.

Experimental results demonstrate that the gamification design framework based on deep learning and robotics significantly improves user engagement and task completion rates. In an experiment involving 100 participants, the overall task completion rate increased by more than 30%. A user satisfaction survey showed that 92% of participants acknowledged the interactivity and enjoyment of the gamification design.

Gamification design, through the organic integration of deep learning and robotics, demonstrates immense potential and innovation.

3.4. Experimental and implementation settings

To enhance the reproducibility of the proposed framework, this subsection details the implementation settings of the core models and the associated experimental protocols. The dataset used in this study includes (i) high-resolution aerial/remote-sensing imagery and (ii) on-site photographs collected in Anhua Village. The imagery covers key rural elements (vegetation, pathways, water bodies, and built structures) and was curated for semantic labeling and model training.

For environmental understanding, DeepLabv3+ was employed for semantic segmentation of rural landscape elements, including vegetation, pathways, water bodies, and built structures. The model was trained using the curated dataset described above, with an approximate training–validation–test split of $70-15-15$. Standard data augmentation techniques, including random cropping and horizontal flipping, were applied. The network was optimized using the Adam optimizer with a learning rate of $1\text{e}-4$ and trained for 50 epochs. Implementation was based on a standard PyTorch pipeline, and training was conducted on a single GPU workstation. Unless otherwise stated, a fixed random seed was used for dataset splitting and training to reduce run-to-run variance.

Generative Adversarial Networks (GANs) were used to synthesize visually coherent landscape scenarios based on extracted semantic features. The generator and discriminator were trained jointly using a combination of adversarial loss and perceptual consistency constraints, enabling the generation of diverse yet ecologically plausible rural scenes.

For multimodal interaction, Wav2Vec 2.0 was adopted for speech recognition to support voice-based human–robot interaction. The model was fine-tuned on a task-specific command dataset related to navigation and interaction instructions; the command set was collected during pilot runs and standardized into a fixed intent/slot schema. Speech recognition performance was evaluated using command recognition accuracy. Reinforcement learning was further applied to optimize robotic path planning and adaptive task recommendation, where the reward incorporated task completion success, time efficiency, and basic interaction signals, functioning as an orchestration layer for robot guidance and task sequencing.

Evaluation was conducted at both the model and system levels. Model-level performance was assessed using standard accuracy-based metrics (e.g., pixel-wise mIoU for semantic segmentation and recognition accuracy for speech commands). System-level effectiveness was evaluated through on-site user studies in Anhua Village using a within-subject comparison between a gamified condition and a non-gamified baseline (“traditional design”), the order of conditions was counterbalanced to reduce learning effects.

4. Gamified applications in rural landscape design

4.1. Gamification and interactive rural landscape design

The application of gamification design in rural landscapes, through the integration of deep learning and robotic interaction systems, aims to provide users with immersive and engaging experiences. By leveraging gamified approaches, traditional rural landscapes can be transformed into dynamic interactive scenes, allowing participants to experience rural features in an entertaining way while enhancing their understanding of rural ecology and culture.

The core of gamification design lies in embedding interactive experiences into landscape planning, making rural landscapes not only visually appealing but also vibrant interactive spaces. This study incorporates virtual reality (VR) and augmented reality (AR) technologies to transform natural elements and cultural heritage in rural areas into digital interactive content. With AR, users can view restoration models of historical buildings in real rural settings and learn about their cultural stories. Meanwhile, VR technology simulates ecological conservation tasks, enabling users to experience the dynamic changes of rural ecosystems from a first-person perspective.

In this study, the “fun” aspect of gamified rural landscape design is understood as a combination of enjoyment, playful challenge, and immersive engagement, arising from task-based interaction, adaptive feedback, and AR/VR-supported experiences.

The implementation of gamification design relies on the coordinated operation of deep learning, robotic interaction, and user feedback mechanisms. This study establishes a modular system architecture comprising a data processing module, task generation module, interaction module, and feedback module. The data processing module extracts key elements of the rural landscape; the task generation module dynamically creates interactive content using deep learning models; the interaction module facilitates multimodal interactions through robots; and the feedback module analyzes user behavior data in real time and provides personalized rewards.

The workflow and functional modules of the entire system are illustrated in Fig. 2.

The implementation of gamification design requires the integration of deep learning, robotics, and user behavior analysis to form a systematic technical workflow. First, the system employs deep learning models for semantic segmentation of remote sensing data, extracting key elements such as farmland, rivers, and vegetation within rural landscapes. Then, personalized task content is dynamically generated based on user behavior data and facilitated through real-time interaction with robots. Finally, the system optimizes user experience through a multimodal feedback mechanism.

The detailed workflow is illustrated in Fig. 3.

The gamification design proposed in this study incorporates task-based interaction, adaptive difficulty mechanisms, and multimodal feedback supported by deep learning and robotic systems. Compared to the traditional design, this gamified approach demonstrates clear advantages in terms of user engagement, task completion rate, and subjective satisfaction.

To validate the practical effectiveness of gamified design in rural landscapes, the study conducted a series of experiments using Anhua Village in Shaoxing City, Zhejiang Province, as the application site.

Anhua Village, a pilot site for Zhejiang Province's “Future

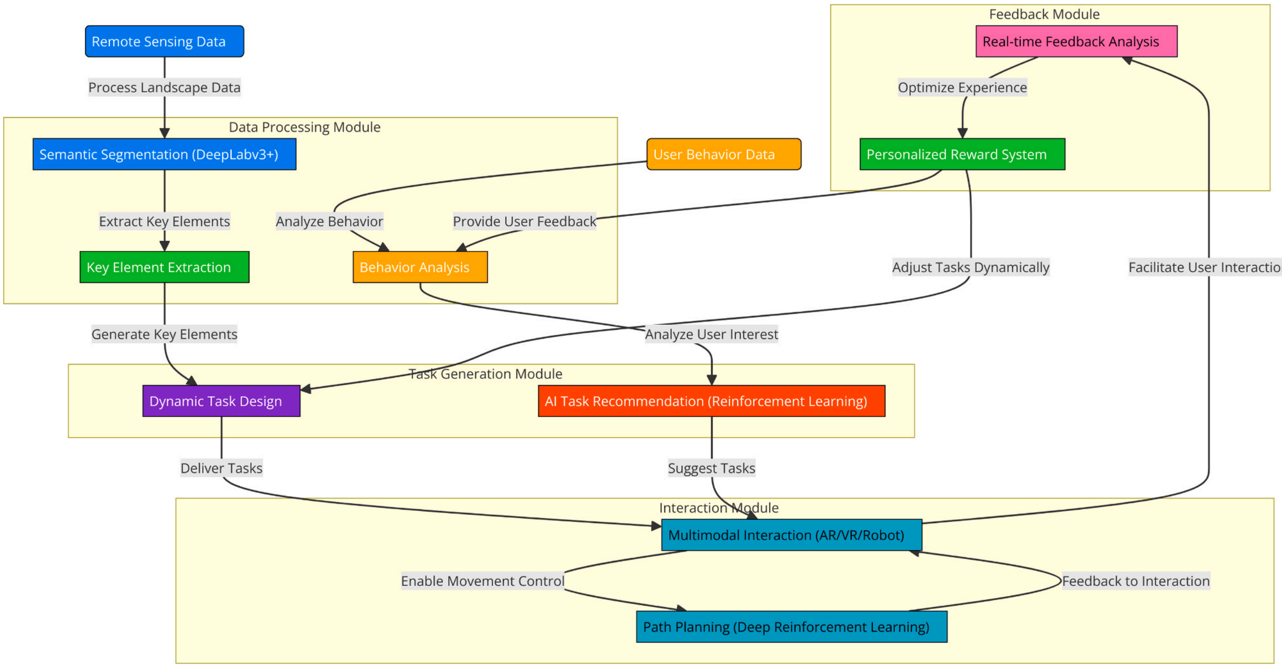


Fig. 2. Schematic Diagram of the System Architecture for Gamified Rural Landscape Design.

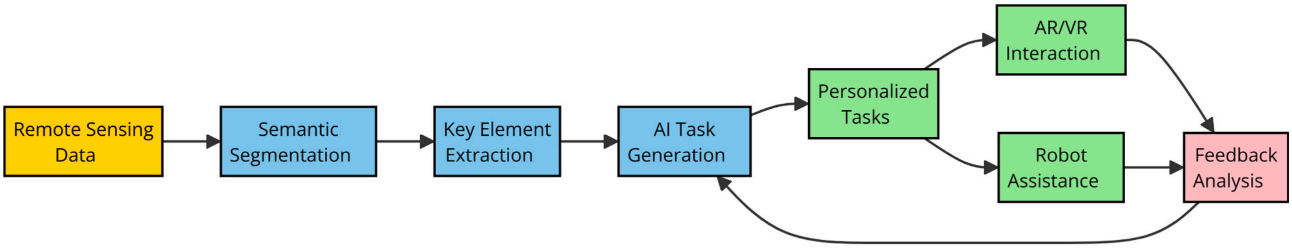


Fig. 3. Schematic Diagram of the Technical Workflow for Gamified Design.

Countryside” initiative and a 3A-level tourist village, boasts excellent infrastructure and rich cultural heritage, making it an ideal platform for implementing gamified landscape design.

The experiments focused on three core tasks—ecological conservation, cultural heritage, and entertainment education—to comprehensively evaluate the user experience and effectiveness of gamified design. A total of 100 participants, including local residents and tourists, were recruited to experience the gamified task system. After completing the tasks, the effectiveness of gamified design was assessed through questionnaires and behavioral data analysis.

The figure illustrates examples of task recommendation and activity selection interfaces (left) and their deployment on a freestanding interactive terminal installed within a traditional pavilion, serving as an on-site entry point that allows users to select and perform ecological, cultural or educational tasks in situ(Fig. 4).

The results suggested improved engagement and satisfaction under the gamified condition. To move beyond a descriptive system report, our evaluation is framed around two empirical questions: (RQ1) whether the proposed gamified framework yields better interaction outcomes than a traditional (non-gamified) baseline, and (RQ2) whether the observed gains are consistent across task types (ecological conservation, cultural heritage, and entertainment education). Accordingly, we report both behavioral metrics (participation rate, completion rate, and stay time) and post-task questionnaire measures, and we explicitly compare the gamified condition with the baseline design as summarized in Table 3.

While Table 3 summarizes descriptive outcomes under the two conditions, inferential statistical analyses were further conducted to examine whether these observed differences were statistically reliable, as reported in Table 4. Specifically, paired-sample t-tests were conducted under the within-subject design at the overall level (N = 100). As shown in Table 4, the gamified condition yielded significantly higher task completion rates, user satisfaction scores, and average stay time compared to the traditional baseline (all $p < 0.001$). Effect sizes (Cohen’s d) indicated large practical effects across all key outcome measures, supporting the robustness of the observed improvements.

Table 3
User experience outcomes in a within-subject comparison between gamified and traditional designs (N = 100).

Indicator	Task Type	Gamified Design (Mean ± SD)	Traditional Design (Mean ± SD)	Δ (Absolute Difference)
User Participation Rate (%)	Overall	85 ± 3.2	65 ± 3.2	+20 pp
	Ecological Protection Task	88 ± 2.5	68 ± 2.5	+20 pp
	Cultural Education Task	82 ± 3.6	62 ± 3.6	+20 pp
Average Task Completion Rate (%)	Overall	90 ± 4.0	70 ± 4.0	+20 pp
	Ecological Protection Task	92 ± 3.8	72 ± 3.8	+20 pp
	Cultural Education Task	88 ± 4.0	68 ± 4.0	+20 pp
User Satisfaction Rating (1–5)	Overall	4.5 ± 0.3	3.8 ± 0.3	+0.7
	Ecological Protection Task	4.6 ± 0.3	3.9 ± 0.3	+0.7
	Cultural Education Task	4.4 ± 0.4	3.7 ± 0.4	+0.7

To clarify how task completion and rewards were determined within the system, Fig. 5 illustrates the in-game feedback interface and the corresponding evaluation and reward mechanism.

The results revealed that, compared to traditional designs, gamified design significantly improved user engagement and task completion rates. User engagement reached 85%, a 20% increase over traditional designs, and task completion rates rose from 70% to 90%. Additionally, user satisfaction scores (on a 5-point scale) increased from 3.8 to 4.5, and the average user stay time in Anhua Village extended by 33%. These

沿河清理垃圾，助力保护生态系统。
目标：收集 10 件垃圾。
提示：使用无人机寻找垃圾。
奖励：+50 经验值和环保徽章。

(a) Task recommendation and activity selection interfaces for ecological,cultural, and educational tasks.

(b) On-site deployment of interactive terminals in outdoor pavilions in Anhua Village.

Fig. 4. On-site deployment of the gamified task interface in Anhua Village.

Table 4
Inferential statistics for the within-subject comparison between gamified and traditional designs (overall, N = 100).

Metric	Gamified (Mean ± SD)	Traditional (Mean ± SD)	Mean Difference	t (df = 99)	p-value	Cohen's d
Task completion rate (%)	90.0 ± 4.0	70.0 ± 4.0	+20.0	15.87	< 0.001	1.59
User satisfaction (1–5)	4.5 ± 0.3	3.8 ± 0.3	+0.7	18.21	< 0.001	1.82
Average stay time (min)	42.3 ± 6.1	31.7 ± 5.8	+10.6	11.04	< 0.001	1.10

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Fig. 5. In-game feedback and evaluation mechanism for gamified tasks.

findings demonstrate that gamified design effectively attracts users and enhances their immersion and interactive experiences in rural landscapes.

During the application process, the study found that ecological conservation tasks were particularly popular among users. Through dynamic task difficulty adjustments and real-time reward mechanisms, users showed a marked increase in enthusiasm for participating in environmental protection activities after task completion. For instance, users involved in trash collection could instantly view the ecological improvements achieved via a virtual system, enhancing their sense of accomplishment and environmental awareness. Cultural heritage activities also received widespread praise, especially the virtual reality reconstruction of ancient architectural processes, allowing users to experience traditional building restoration as "craftsmen." Participants generally found this design both enjoyable and educational, helping them better understand traditional culture. Educational and entertainment tasks successfully combined learning with interaction. Users identified plants through augmented reality (AR) technology and received real-time ecological information, making the learning process both engaging and practical. A deeper analysis of the experimental data indicates that gamified design not only enhances user engagement but also significantly improves the overall user experience and enjoyment.

4.2. *Gamified design of public facilities in rural areas*

Rural public spaces serve as both carriers of cultural resources and central venues for recreation and leisure. Gamified design infuses public facilities with interactivity and educational value, transforming them from traditional static displays into dynamic participatory media.

In this study, gamified elements were integrated into public facilities such as farmlands and rural parks in Anhua Village, turning these rural public spaces into multifunctional venues that combine education, entertainment, and cultural heritage. This transformation injects new vitality into rural revitalization efforts.

The research team implemented gamified design for an ecological experience trail (Fig. 6). A dynamic interactive trail supported by augmented reality (AR) technology was constructed, connecting multiple functional nodes along the path. Each node features unique task-based scenarios. At the wetland node, users can use AR devices to observe virtual models of water quality changes and complete a "vegetation restoration" task to rehabilitate the wetland ecosystem. At the vegetation observation point, users can scan surrounding plants using interactive devices to gain real-time insights into their ecological functions and cultural significance.

These nodes are connected through a linear narrative along the trail, creating a cohesive learning and entertainment experience. The design of the entire trail enables users to immerse themselves as active participants in rural ecological conservation. The ecological experience trail shown in Fig. 6 represents a design-oriented illustration of the interactive sequence and spatial organization from the system perspective.

In Anhua Village, rural public spaces such as village paths, farmland edges, and activity areas are enhanced through augmented reality (AR)–based gamified installations that support on-site exploration and informal learning. These AR applications digitize key agricultural and ecological information and overlay it onto real rural environments, enabling users to engage with farming-related knowledge while remaining embedded in the physical landscape.

A representative example is the "Plant Identification Challenge," in which users scan real vegetation using mobile or lightweight wearable AR devices to access contextual information on plant species, growth characteristics, and agricultural functions. Users are invited to complete short, knowledge-based quiz tasks linked to virtual rewards, encouraging active participation and learning. As illustrated in Fig. 7, these AR activities are implemented during public events and educational programs, including the Second Anhua Village Vegetable Festival (2025) and primary school study tours. The design emphasizes accessibility and

(a) Design-oriented interface for the ecological experience trail system

(b) On-site photos of tourists participating in ecological experience and interactive activities

Fig. 6. System interface and on-site participation of the ecological experience trail.

Fig. 7. The AR interactive activity scene of the rural park in Anhua Village.

public participation, allowing users of different age groups to interact with AR content in real rural settings.

Meanwhile, the “Interactive Guide Robot” enables real-time human–robot interaction in open rural public spaces through integrated voice and gesture recognition technologies (Fig. 8). As shown in the figure, the robot operates in village plazas and pedestrian areas, accompanying visitors at walking speed and responding to spoken commands or simple gestures. This mobile interaction mode allows the robot to provide basic navigation assistance, site-specific information, and activity guidance without requiring users to operate handheld devices. By supporting hands-free and intuitive interaction in an outdoor environment, the robot is particularly suitable for first-time visitors, elderly users, and group-based activities, thereby enhancing the accessibility and inclusiveness of gamified rural experiences.

The application of gamification and multimodal interaction technologies in public facilities has brought innovation and vitality to the interactive experiences in rural parks. These facilities not only serve functional purposes but also act as engaging entertainment platforms. During interactive sessions, users can directly interact with the facilities through voice commands or touch controls, selecting ecological information or completing specific gamified tasks. This multimodal interaction seamlessly integrates gamification concepts, enhancing usability while significantly boosting user engagement and enjoyment through entertaining task mechanisms. It effectively sparks users’ curiosity and enthusiasm for participation.

Experimental results demonstrate that these gamified facilities achieve notable success in increasing user engagement, improving educational outcomes, and supporting environmental management. Over a three-month experiment involving six participants, more than 85% reported that the facilities enhanced their understanding of rural ecology

Fig. 8. The Anhua Village Rural interactive robot guides visitors.

and culture. Additionally, 75% rated the tasks as highly enjoyable.

User feedback was collected using a structured questionnaire administered after task completion. The questionnaire consisted of three components: (i) perceived engagement and enjoyment, (ii) perceived usability and interaction comfort, and (iii) overall satisfaction with the gamified experience. Responses were recorded using a five-point Likert scale, complemented by optional open-ended comments. For the longitudinal study with six participants, the same questionnaire framework was applied at multiple time points, together with observational notes documenting interaction frequency and qualitative behavioral changes.

As shown in Fig. 9, an analysis of participants' emotional values revealed high initial values, attributed to their sense of novelty and fun during the interactions. This heightened anticipation for subsequent content contributed to sustained engagement.

During the experience, an overall emotional curve was plotted by connecting the emotional values of each sub-process (see Fig. 10). This curve indicates that participants' emotional values were relatively low at the beginning of the interaction but gradually increased as gamified tasks progressed, remaining at a high level during the middle and later stages, and slightly declining at the end of the experience.

This finding suggests that the gamified task design plays a critical role in enhancing user emotions and provides empirical support for the fun/enjoyment dimension of the proposed gamified experience.

Although the empirical validation of this study is based on the case of Anhua Village, the proposed gamified rural landscape design framework is not confined to a single geographic or cultural context. From a technical perspective, the framework adopts a modular architecture in which core components—such as semantic perception, task generation, multimodal interaction, and feedback mechanisms—can be reconfigured or scaled according to local data availability and infrastructural conditions. At the same time, socio-cultural factors, including local traditions, cultural narratives, and community participation patterns, may vary significantly across rural regions, implying that gamified task themes and interaction strategies should be contextually adapted rather than directly replicated. Therefore, the proposed framework should be understood as a transferable design methodology rather than a one-size-fits-all solution.

5. Conclusion

With the rapid advancement of technology, deep learning and robotics have brought unprecedented potential and vitality to rural landscape design. Traditional rural landscape design is often limited to static planning and presentation, lacking sufficient interactivity. By integrating deep learning and robotics, rural landscape design is evolving towards greater intelligence, interactivity, and gamification. This

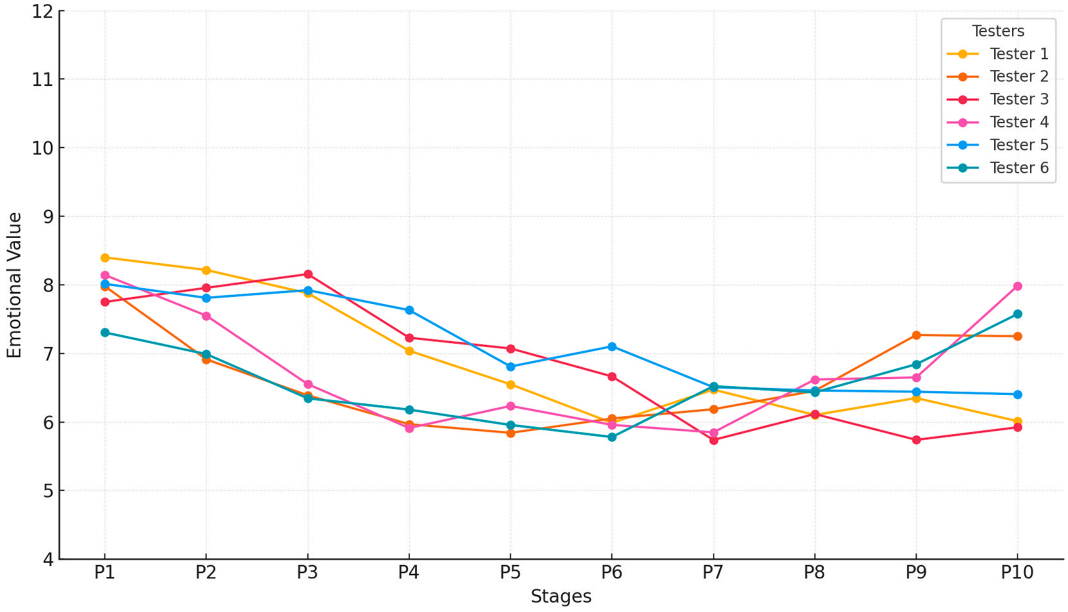

Fig. 9. Emotional Value Trends Across Testers.

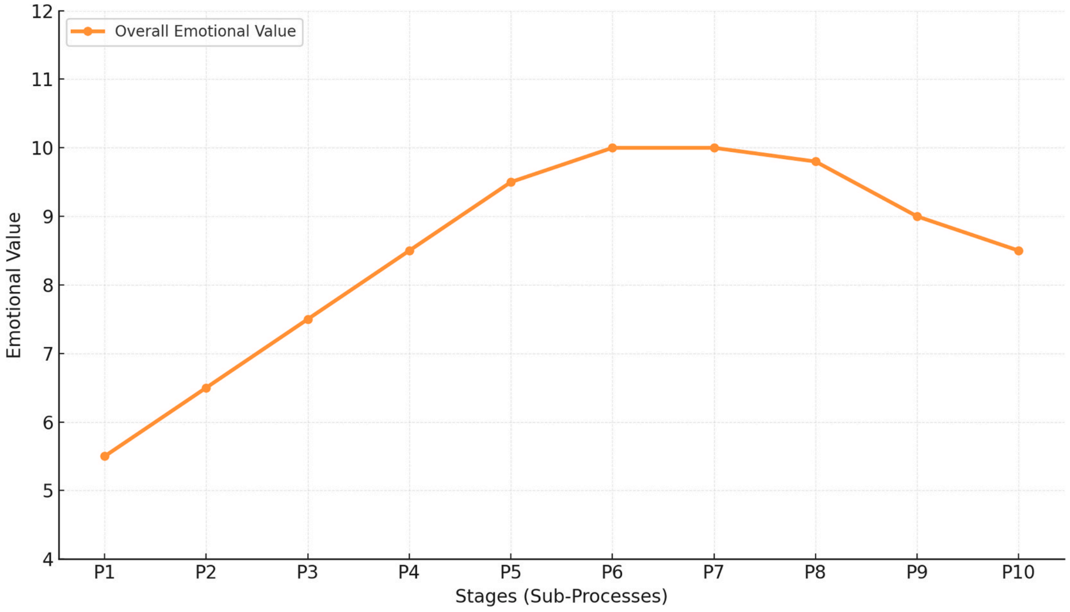

Fig. 10. Overall Emotional Curve Across Sub-Processes.

innovative approach not only redefines the form of rural landscape design but also significantly enhances the dissemination of rural culture and the efficiency of ecological conservation.

In gamified rural landscape design, deep learning technologies provide solid support for precise modeling and data processing. Through semantic segmentation of remote sensing imagery and generative adversarial networks (GANs), ecological elements in rural landscapes are highly restored and optimized. Robotics plays a critical role in enabling dynamic interaction. This integrated approach not only creates enriched interactive experiences for visitors but also inspires user engagement through task-driven gamified design, enhancing the recreational and cultural value of rural landscapes.

The gamified rural landscape design framework proposed in this study injects new momentum into rural revitalization and sustainable development. By generating personalized tasks through deep learning algorithms and integrating augmented reality (AR) and virtual reality (VR) technologies, users can complete thematic tasks such as ecological conservation, cultural heritage, and educational entertainment in an environment blending virtual and real elements.

Continuous advancements in deep learning and robotics will open broader application scenarios for rural landscape design. From multimodal data integration to task generation optimization, dynamic interaction design to ecosystem management, the combination of technology and design will create more engaging, meaningful, and sustainable rural landscapes. This will provide residents and visitors with richer and more attractive experiences, offering strong technical support and practical examples for the implementation of rural revitalization strategies.

CRediT authorship contribution statement

Ya Li: Writing – original draft, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Faridah Sahari:** Writing – review & editing, Supervision, Methodology, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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