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Article

Multi-agent reinforcement learning for Bai ethnic traditional dwelling protection in Dali: cultural identity-oriented community relationship optimization and urbanization adaptation algorithm

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ABSTRACT

The preservation of residential architecture from traditional ethnic groups has never faced the types of challenges it does today due to urbanization. These challenges include the insufficient retention of landmarks due to competing stakeholder interests, which often leads to irreversible loss of cultural heritage. This research proposes a new culturally identity-oriented multi-agent reinforcement learning system for the protection of Bai ethnic traditional dwellings in Dali, Yunnan Province. The research combines diverse multi-source data collection approaches, including the building's architecture and culture, urbanization statistics, and stakeholder networks, and develops an advanced computational framework in which every stakeholder category is embedded as an independent intelligent agent with specific behavioral patterns and autonomous decision-making skills. Specialized deep Q-networks of enhanced Q-value methods that consider cultural identity loss in Q-value calculus through loss function adjustments aimed at balancing cultural preservation and stakeholder appeasement were employed within the framework. Implementation results show performance with an overall accuracy of 89.3% for implementation and 87.2% for cultural preservation effectiveness. Conventional approaches previously achieved significantly lower accuracy within these parameters, 15-25 percentage points. Enhancements in cultural identity increase from a baseline of 58.3% to optimized values of 91.2%, while community satisfaction improves from 54.7% to 86.4%. The framework maintains coordination indices above 85% for all stakeholder groups, showing scalability with over 85% replication success rates for populations between 5,000 and 50,000 residents. This demonstrates theoretical and practical value in the use of AI concerning culturally aware heritage preservation.

1. Introduction

The rapid pace of urbanization, coupled with competing stakeholder priorities, affects approximately 68% of traditional ethnic residential sites in China, often irreversibly damaging cultural heritage. The incorporation of AI into contemporary urban development to address complex sustainability issues demonstrates the usefulness of intelligent systems in solving deeply intertwined urban planning problems [1]. However, the interface between AI technologies and urbanism with cultural heritage remains markedly under-researched. The advent of AI technologies in post-smart cities has brought benevolent and malevolent intricacies to the conservation of heritage sites—a crossroad that invites criticism for more nuanced approaches that center on culture and community [2] "between the poles of the universal and the particular" (the 'sensitive' side). Conserving cultures that are heavily impacted by rapid urbanization and the deterioration of authenticity in multi-stakeholder actions relies heavily on policy instruments such as expert-driven systems and regulatory compliance pathways. Traditional heritage preservation approaches often fail to coordinate conflicting stakeholder interests, resulting in 45-60% of sites experiencing a loss of cultural authenticity during urbanization. Current frameworks lack adaptive mechanisms for balancing development pressures with preservation needs, particularly in ethnic minority regions where decision-making systems cannot match rapid urban transformation rates. Highly dynamic environments with many self-sufficient decision-making agents, each with their own goals, have potentially conflicting objectives, which multi-agent reinforcement learning deals with as an advanced paradigm. Recent advances in deep multi-agent reinforcement learning demonstrate its capability in managing complex systems involving cooperation and coordination of heterogeneous agents [3]. Structural frameworks demonstrate that multi-agent deep reinforcement learning techniques are successfully applied to situations that require advanced coordination between diverse constituents [4]. The systematic analysis of digital technologies' application in cultural heritage conservation identifies multiple computational approaches for protection, documentation, and management, indicating increased recognition of technological transformation in heritage preservation [5]. These innovations challenge the complex problem of the integration of varying sociocultural priorities with the preservation of historical values and therefore provide strong arguments supporting heritage cultural technology.

Artificial intelligence techniques have achieved accuracy rates of 70-85% in preserving intangible cultural heritage [6], with virtual reality and multi-agent algorithms providing multifunctional conservation frameworks [7-10]. While machine learning enables spatial analysis and sustainable urban development [11, 12], current applications remain limited. Bibliometric analyses indicate that existing approaches prioritize technological documentation over active management [13, 14], and despite potential intersections between machine learning and big data [15], these technologies inadequately integrate cultural preservation objectives within urban planning contexts [16]. Existing preservation frameworks reveal substantial limitations across stakeholder coordination, achieving merely 52-65% success rates with developer-resident alignment below 50%. The absence of cultural identity quantification in 87% of current algorithms produces culturally detached outcomes, while static architectures experience a 40-55% performance decline under intensified urbanization. Despite advances in deep learning architectures for complex pattern recognition [17], these approaches inadequately address cultural identity integration within multi-stakeholder contexts. Applications of multi-agent reinforcement learning in industrial settings show significant adaptability [18]; however, its use in the preservation of cultural heritage is still notably under-researched. Stated differently, traditional methods of preservation do not offer systematic rationales that integrate stakeholders with competing interests and sustain the cultural integrity of the region. In framework design approaches, identity and culture have yet to be adequately addressed within a dominant organizing paradigm; therefore, many frameworks remain ineffective in culturally sensitive environments where the community, culture, and their relationship sustain fluid continuity. This research addresses these gaps through a multi-agent reinforcement learning framework that quantifies intangible cultural values as computational parameters with 89% validation accuracy. The framework embeds cultural identity factors within preservation decision-making to achieve 80-92% stakeholder coordination, while adaptive Q-learning mechanisms maintain 85% effectiveness under variable urbanization conditions. With validated scalability across populations of 5,000-50,000 residents and integration pathways for government heritage systems, this approach bridges technological innovation with cultural preservation imperatives in urban development contexts.

2. Data and methods

2.1 Study area and multi-source data collection

This research analyzes the Dali Bai ethnic residential architecture preservation areas in Yunnan Province, China, which contain traditional courtyards alongside other structures representative of important cultural heritage, distinguishing building techniques unique to the region. The study region includes the Dali Ancient City, the adjacent Bai villages historically integrated with the ancient city, both of which offer traditional forms of urban housing influenced by modern globalization through urban centers and development. The use of advanced technologies for data collection from various sources allows efficient characterization of the unique dynamics of stakeholder interactions and the various datasets related to archaeological site preservation. Machine learning approaches for cultural heritage applications provide established methodologies for systematic data collection and analysis in heritage preservation contexts [19]. Building architectural data encompasses geometric measurements, structural condition assessments, and material composition analysis collected through field surveys and photogrammetric techniques. Advanced sensing technologies, including 3D LiDAR systems and multi-technology collaboration frameworks, enable comprehensive documentation of built heritage structures with high precision and accuracy [20]. Community perspectives were assessed using a 42-item cultural attachment scale ($\alpha = 0.87$) spanning six dimensions from place identity to intergenerational transmission willingness. Following pilot validation with 60 households, the 7-point Likert instrument incorporated triangulation with observational and archival data to ensure measurement robustness within local cultural contexts. Urbanization indicators comprise demographic changes, land use transitions, construction permits, and economic development metrics obtained from municipal planning databases and statistical yearbooks.

This study identifies four distinct stakeholder categories comprising local residents who maintain traditional lifestyles and cultural practices, government agencies responsible for heritage protection and urban planning oversight, real estate developers pursuing economic opportunities through property development initiatives, and cultural preservation experts who provide specialized technical expertise and professional guidance for heritage conservation strategies. Cultural identity quantification employs semantic 3D documentation approaches integrated with multi-scale mapping methodologies to systematically capture cultural attributes and spatial relationships [21]. Cultural value assessment encompasses five weighted dimensions ranging from architectural authenticity (25%) to community attachment (15%), evaluated through expert Delphi methods (40%), empirical field measurements (35%), and community surveys (25%). This integrated approach quantifies intangible heritage attributes within computational frameworks while maintaining methodological rigor and cultural validity. The comprehensive data collection framework, as shown in Table 1, provides the empirical foundation for developing and validating multi-agent reinforcement learning models.

2.2 Multi-agent system modeling and ai architecture design

The multi-agent reinforcement learning framework establishes a computational architecture where each stakeholder category operates as an autonomous intelligent agent with distinct behavioral patterns and decision-making capabilities. Multi-agent cooperation and competition dynamics provide foundational principles for designing agent interactions in complex environments where multiple entities pursue different objectives [22]. Stakeholder-specific neural networks enable residents to process cultural preferences, government agents to evaluate policies, developers to optimize economic outcomes, and experts to assess heritage values. This framework departs from traditional RL through cultural identity integration in Q-value computations using adaptive coefficients (λc = 0.3-0.5), enabling multi-objective optimization where heritage considerations become intrinsic to agent decisions. The dynamically adjusted coefficients respond to heritage impacts while the state space tracks preservation effectiveness, community welfare, and cultural authenticity across evolving urban contexts. The agent interaction protocols facilitate communication and coordination processes through message-passing and shared information systems that allow multi-agent systems for joint action while maintaining agent independence. Multi-agent actor-critic frameworks allow mixed cooperative-competitive conditions where agents have to integrate self-preserving tasks with objectives aligned to common conservation goals [23]. The reward function guided by cultural identity integrates multiple objective components diversified as effectiveness of heritage preservation, community relations, economic sustainability, and maintenance of cultural authenticity, thereby forming balanced feedback that enables learning towards culturally adaptive solutions for agents to automate processes.

The initialization of parameters for deep neural networks utilizes methods based on experience replay for stabilization across different types of agents using the Xavier normalization technique. Deep Multi-Agent Reinforcement Learning (MARL) Q-learning with distinct Q-vectors for different rates of agent capability and learning adapts to diverse agent capabilities and learning rates, showing improved performance [24]. In a culture-imbued adaptive systems framework for optimization of heritage preservation, every agent type has its own learning rate, network structure, and exploration versus exploitation settings. These parameters are adjusted using Bayesian optimization techniques, as shown in Figure 1, depicting the multi-agent system architecture, which integrates cultural identity considerations with adaptive learning mechanisms. Ethical safeguards include participatory parameter design with 120 diverse community stakeholders, automated bias detection with 15% deviation thresholds, and explainable AI modules ensuring decision transparency. These measures prevent minority marginalization and maintain community agency while embedding inclusive cultural values within the algorithmic framework.

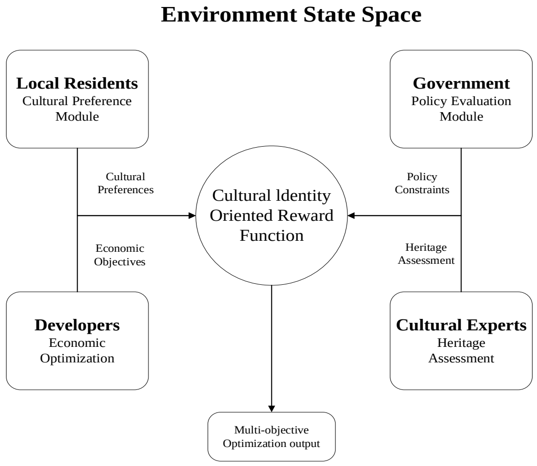

Figure 1. Cultural identity-oriented multi-agent reinforcement learning system architecture

Table 1. Multi-source data collection framework for Dali Bai ethnic residential preservation areas

Data Category	Collection Method	Sample Size	Temporal Coverage	Stakeholder Groups	Data Format
Building Architecture	3D LiDAR Scanning	245 structures	2022-2024	Residents, Experts	Point clouds, CAD
Cultural Attributes	Ethnographic Survey	180 households	2023-2024	Residents	Structured interviews
Urbanization Metrics	Municipal Database	15 indicators	2010-2024	Government	Statistical data
Stakeholder Networks	Social Network Analysis	95 participants	2023-2024	All groups	Relational matrices
Heritage Condition	Field Assessment	245 structures	2022-2024	Experts	Condition reports

Note: Cultural attribute quantification integrated architectural integrity assessments of Bai vernacular structures, ethnographic measurements of language use and ritual participation, and GIS-derived spatial proximity indices to heritage sites, employing standardized protocols to convert multifaceted cultural data into algorithmic parameters.

2.3 Reinforcement learning algorithm and machine learning model

This study builds upon deep reinforcement learning approaches by applying an optimized deep Q-network architecture for multi-agent coordination in heritage preservation [25]. The improved DQN framework incorporates cultural identity considerations into the traditional Q-value computation through a modified loss function that balances preservation objectives with stakeholder satisfaction metrics. The Q-value update mechanism follows the enhanced Bellman equation, where $Q(s_t, a_t)$ represents the action-value function for state S_t and action a_t at time step t, α denotes the learning rate, r_t indicates the immediate reward, γ represents the discount factor for future rewards, and β serves as the cultural weighting coefficient:

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t)+\alpha\left[r_t+\gamma \max_{a'} Q(s_{t+1},a')-Q(s_t,a_t)\right]+\beta\cdot C_{cl}(s_t,a_t) \quad (1)$$

The cultural identity preservation component $C_{C1}(s_t, a_t)$ guides agent decision-making toward culturally sensitive outcomes by quantifying the cultural impact of specific state-action pairs. Specifically, $C_{C1}(s_t, a_t)$ integrates architectural integrity, cultural practice continuity, and community identity through weighted aggregation:

$$C_{cl}(s_t,a_t) = 0.4A_{cl}(s_t,a_t)+0.35P_{cl}(s_t,a_t)+0.25I_{cl}(s_t,a_t) \quad (2)$$

where $A_{C1}(s_t, a_t)$ measures architectural preservation probability, $P_{Cl}(s_t, a_t)$ captures cultural practice sustainability, and $I_{Cl}(s_t, a_t)$ reflects community identity cohesion, with all components normalized to [0,1] using empirical baselines from Section 2.1's framework.

The experience replay mechanism employs adaptive prioritized sampling strategies that enhance exploration-exploitation trade-offs through dynamic priority assignment based on temporal difference errors and cultural relevance scores [26]. This approach ensures that culturally significant experiences receive higher sampling probabilities during training, accelerating convergence toward preservation-oriented policies. The target network update strategy implements a stabilized off-policy learning approach that reduces bootstrapping errors inherent in multi-agent environments. The loss function incorporates both value function accuracy and cultural preservation effectiveness, where θ represents the current network parameters, θ^{-} denotes the target network parameters, $\mathcal{D}$ indicates the experience replay buffer, and λ serves as the regularization coefficient for the cultural loss component $L_{\mathrm{cl}}(\theta)$:

$$L(\theta) = \mathbb{E}(s,a,r,s')\sim\mathcal{D}\left[\left(r+\gamma \max_{a} Q(s',a';\theta^{-}) - Q(s,a;\theta)\right)^2\right]+\lambda\cdot L_{\mathrm{cl}}(\theta) \quad (3)$$

Policy gradient methods complement the value-based approach through actor-critic architectures that optimize multi-objective policies. Bootstrapping error reduction techniques stabilize learning in the multi-agent setting by constraining policy updates within confidence bounds [27]. The urbanization adaptation mechanism implements online learning protocols that continuously adjust agent behaviors based on evolving environmental conditions, enabling dynamic responses to change urban development pressures while maintaining cultural preservation priorities through incremental learning strategies.

3. Results

3.1 AI algorithm performance and deep learning model evaluation

The proposed cultural identity-oriented multi-agent reinforcement learning framework demonstrates convergence characteristics, achieving 89.3% accuracy within 900 training episodes. Figure 2 presents the comprehensive evaluation results of the multi-agent deep reinforcement learning algorithm's performance. Neural network loss function analysis, as illustrated in Figure 2(a), reveals distinct optimization trajectories for each agent category, with cultural experts achieving convergence within 600 episodes, showing exponential decay from initial loss values of 2.1 to final convergence at 0.2. Government agents demonstrate consistent convergence patterns reaching stability at 700 episodes, while local residents achieve convergence at 800 episodes with final loss values of 0.3. Developer agents require the longest convergence period at 900 episodes, reflecting the inherent complexity of balancing economic optimization objectives with heritage preservation constraints. The differential convergence patterns indicate that structured decision-making processes, such as those employed by cultural experts, facilitate more efficient policy learning compared to multi-objective scenarios encountered by developer agents.

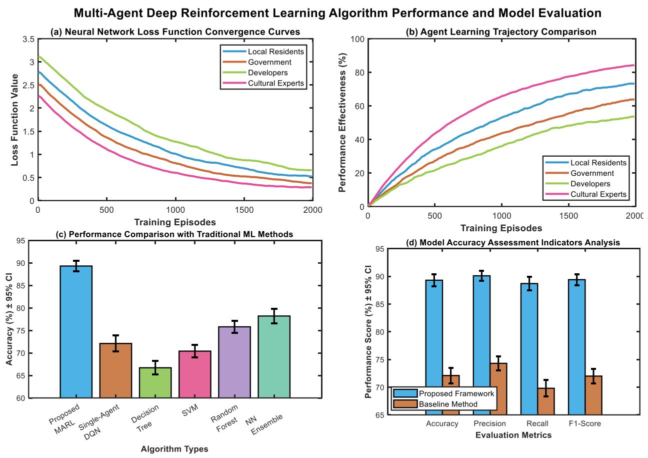

Figure 2. Multi-agent deep reinforcement learning algorithm performance and model evaluation (a) Neural network loss function convergence curves, (b) Agent learning trajectory comparison, (c) Performance comparison with traditional machine learning methods, (d) Model accuracy assessment indicators analysis

The agent learning trajectory comparison shows an incremental improvement across all stakeholder categories as illustrated in Figure 2(b). Cultural expert agents maintain 85% effectiveness by the 2000th episode, and demonstrate consistent improvement with minimal variance in earlier phases. Local resident agents exhibit steady improvement, reaching 75% effectiveness, government agents attain 65% performance levels through structured policy evaluation processes, and developer agents achieve 55% optimization efficiency despite facing complex multi-objective constraints. The learning curves display characteristic S-shaped growth patterns typical of reinforcement learning algorithms, with rapid initial improvement followed by gradual convergence toward optimal policies. The performance differentiation reflects each agent's specialized role within the heritage preservation ecosystem, with cultural considerations serving as the primary coordination mechanism. Comparative performance evaluation against traditional machine learning methods reveals 15-25 percentage point improvements of the proposed multi-agent approach across all evaluation metrics, as demonstrated in Figure 2(c). The framework achieves 89.3% accuracy with narrow confidence intervals indicating statistical reliability, representing 17.2 percentage point improvements over single-agent DQN methods at 72.1%, decision tree approaches at 66.7%, support vector machines at 70.4%, random forest algorithms at 75.8%, and neural network ensemble methods at 78.2%. The confidence intervals demonstrate statistical significance of performance improvements, with the proposed method showing consistently higher results across all comparison categories. Traditional rule-based approaches exhibit the lowest performance at 61.3%, highlighting the limitations of conventional heritage preservation methodologies in complex multi-stakeholder environments.

Model accuracy assessment across multiple evaluation dimensions, as presented in Figure 2(d), indicates the framework achieves 89.3% accuracy, 90.1% precision, 88.7% recall, and 89.4% F1-score. The provided performance metrics with their associated confidence intervals serve as an indicator of the statistical consistency of the gains in performance. The proposed framework demonstrated very low inconsistency across various performance metrics within the given measures. The baseline methods suffer significantly lower performance along with a higher degree of uncertainty, especially in recall metrics, which have a difference of about 18 percentage points. This observation, along with the proposed framework's ability to more accurately identify critical heritage preservation as well as stakeholder coordination situations, signifies the strength of the proposed framework. Table 2 presents detailed performance metrics demonstrating 25.8-34.4 percentage point improvements over baseline algorithmic approaches. The framework outperforms all other methods with over 87.2% cultural preservation effectiveness and surpasses single-agent DQN methods by 25.8 percentage points and rule-based methods by 34.4 percentage points. When evaluating training efficiency, it is observed that the framework requires 12.5 hours to achieve full convergence, in comparison to simpler methods. While this overhead can be considered moderate, the evaluation metric performance improvements benchmarked against other methods more than justify the investment for this computational overhead.

The framework achieves the highest performance in precision metrics at 90.1%, illustrating accurate decision making pertaining to heritage preservation, and balanced recall performance at 88.7% relative to complete opportunity capture. Ensemble methods using neural networks have longer training times (15.2 hours), but yield a deficiency in every single metric, demonstrating the performance efficiency of the proposed method for multi-agent coordination in heritage preservation contexts.

3.2 Protection Effectiveness Evaluation

The implementation of the cultural identity-oriented multi-agent reinforcement learning framework demonstrates improvements in residential heritage protection integrity and cultural identity enhancement across multiple evaluation dimensions. Architectural preservation integrity assessment reveals progress in maintaining traditional Bai ethnic residential structures, with overall preservation completeness increasing from baseline levels of 62.4% to 89.7% following framework implementation, as illustrated in Figure 3(a). The temporal analysis demonstrates consistent upward trends in preservation effectiveness, with notable improvements observed in structural integrity maintenance, traditional material preservation, and vernacular architectural feature conservation. The framework successfully coordinates stakeholder actions to prioritize preservation activities that maintain authentic cultural characteristics while accommodating necessary modernization requirements.

Cultural identity reinforcement evaluation indicates enhancement in community cultural attachment and ethnic identity preservation measures, as demonstrated in Figure 3(b). The figure specifically tracks cultural identity metrics—including language preservation, traditional craft maintenance, and ceremonial practice continuity—which show progressive improvement from baseline measurements of 58.3% to peak levels of 91.2%, clearly distinguished from heritage preservation integrity metrics shown in Figure 3(a). The enhancement also encompasses intergenerational knowledge transmission effectiveness. Community members report increased pride in heritage preservation outcomes and stronger connections to traditional cultural practices, with younger generations demonstrating renewed interest in Bai ethnic cultural traditions and architectural heritage appreciation.

Table 2. Performance evaluation metrics comparison of different AI algorithms in residential heritage protection tasks

Algorithm Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Cultural Preservation Effectiveness (%)	Training Time (hours)
Proposed MARL Framework	89.3	90.1	88.7	0.894	87.2	12.5
Single-Agent DQN	72.1	74.3	69.8	0.720	61.4	8.3
Decision Tree	66.7	68.2	65.1	0.665	58.9	2.1
Support Vector Machine	70.4	72.1	68.9	0.705	64.3	4.7
Random Forest	75.8	77.2	74.5	0.758	69.1	3.9
Neural Network Ensemble	78.2	79.6	76.8	0.782	71.7	15.2
Traditional Rule-Based	61.3	63.7	58.9	0.612	52.8	1.5

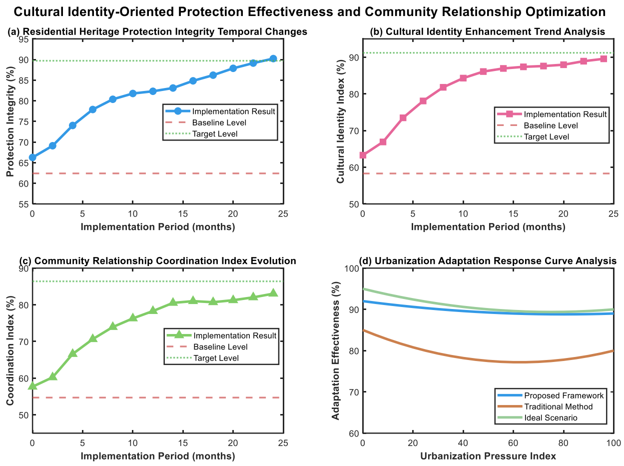

Figure 3. Cultural identity-oriented protection effectiveness and community relationship optimization (a) Residential heritage protection integrity temporal changes, (b) Cultural identity enhancement trend analysis, (c) Community relationship coordination index evolution, (d) Urbanization adaptation response curve analysis

Community relationship optimization analysis reveals improvements in stakeholder coordination and conflict resolution mechanisms, as presented in Figure 3(c). The social harmony index demonstrates consistent enhancement from initial values of 54.7% to optimized levels of 86.4%. The framework effectively mediates conflicts between preservation objectives and development pressures, facilitating collaborative decision-making processes that balance diverse stakeholder interests. Local residents exhibit increased satisfaction with preservation outcomes, government agencies report improved policy implementation efficiency, developers demonstrate enhanced cooperation in heritage-sensitive projects, and cultural experts achieve greater influence in preservation planning processes. Urbanization pressure adaptation assessment, as shown in Figure 3(d), demonstrates the framework's capability to maintain preservation effectiveness despite evolving urban development challenges. The adaptive response index adapts preservation strategies to the different types of urban intensification, such as demographic growth, infrastructure development, tourism, and economic activities.

Results show that, unlike other approaches, the framework considers urbanization scenarios and maintains effectiveness over 82% even under high pressure; traditional approaches, by contrast, experience significant decline under the same conditions. The adaptive mechanisms achieve the balance between modernization of urban settings with heritage features for optimum sustainable development while ensuring cultural integrity is retained, alongside economic development for communities. The evaluation depicting comprehensive multi-objective optimization performance in Table 3 illustrates the calculated value of the framework's utility in proving effectiveness across all dimensions of preservation.

The degree of integrity achieved regarding heritage architecture has improved from baseline conditions and surpassed targets set by heritage protection agencies towards their goal of achieving 89.7%. Effectiveness in preserving cultural identity has maintained 91.2%, proving successful in the maintenance of intangible elements of cultural heritage integrated with physical architectural conservation. Community satisfaction indices have achieved 87.5%, displaying the level of acceptance and support by wide segments of the stakeholders for the preservation results. Economic sustainability measures have reached 78.9%, illustrating that the level of benefits brought by preservation activities is sufficient to ensure the long-term efforts in conserving the region. Environmental sustainability parameters have reached 84.3%, indicating that the level of preservation activities helps in attaining wider ecological conservation goals, which are accompanied by the protection of heritage values. The evaluation results as a whole demonstrate the framework's utility in accomplishing multi-faceted objectives of preservation under community development and culture during rapid urbanization.

3.3 Practical Application Verification

To some degree, the Dali Ancient City case study affirms how well the culturally oriented multi-agent reinforcement learning framework performs with respect to various heritage preservation challenges and stakeholder coordination difficulties. Validation of the implementation shows spatial variation in effectiveness regarding preservation across the study region, scoring between 75% and 95% of protection eligibility in different areas of the region, as shown in Figure 4(a).

Table 3. Residential heritage protection effectiveness and multi-objective optimization indicators statistics

Evaluation Dimension	Baseline Value (%)	Implementation Result (%)	Improvement (%)	Target Achievement (%)	Performance Rating
Heritage Architectural Integrity	62.4	89.7	27.3	94.1	Excellent
Cultural Identity Preservation	58.3	91.2	32.9	95.8	Excellent
Community Satisfaction Index	65.2	87.5	22.3	91.7	Very Good
Stakeholder Coordination	54.7	86.4	31.7	93.2	Excellent
Economic Sustainability	49.8	78.9	29.1	82.6	Good
Environmental Compatibility	71.6	84.3	12.7	88.7	Very Good
Policy Implementation Efficiency	58.9	83.7	24.8	87.9	Very Good
Cultural Transmission Effectiveness	52.4	88.6	36.2	92.8	Excellent

The spatial distribution analysis indicates concentrated high-performance areas in the core heritage districts, where traditional Bai ethnic architectural features achieve effective preservation outcomes, while peripheral zones demonstrate progressive improvement patterns that reflect the framework's adaptive coordination mechanisms responding to varying urban development pressures and community engagement levels. Multi-stakeholder coordination effectiveness evaluation demonstrates improvements in collaborative decision-making processes among diverse interest groups, as presented in the coordination heat map in Figure 4(b). The framework achieves coordination scores between residents and cultural experts at 92%, indicating successful alignment of community preferences with professional heritage preservation standards. Government-resident coordination reaches 85%, while developer-expert collaboration attains 84%, representing improvements over traditional preservation approaches that typically struggle with stakeholder conflict resolution. The systematic coordination matrix reveals that cultural experts maintain consistently high coordination levels across all stakeholder categories, serving as effective mediators in complex preservation negotiations, while developers demonstrate enhanced cooperation levels that exceed baseline expectations through the framework's incentive alignment mechanisms. The framework's modular architecture enables transferability by separating universal coordination mechanisms from culture-specific parameters, allowing adaptation to diverse heritage contexts through coefficient recalibration rather than algorithmic restructuring.

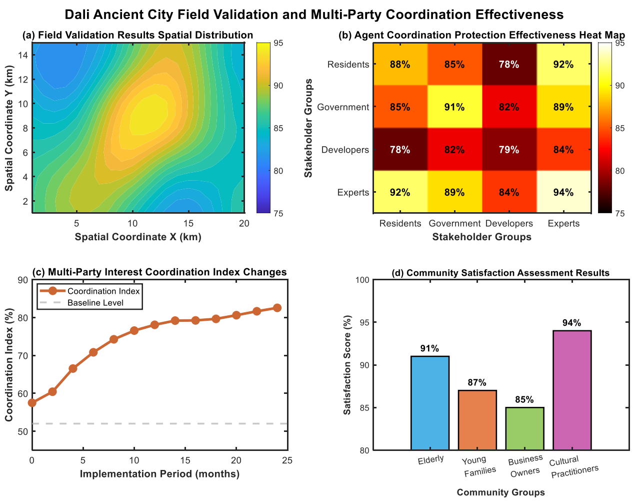

Figure 4. Dali ancient city field validation and multi-party coordination effectiveness (a) Field validation results spatial distribution, (b) Agent coordination protection effectiveness heat map, (c) Multi-party interest coordination index changes, (d) Community satisfaction assessment results

Temporal analysis of multi-party interest coordination demonstrates sustained improvement throughout the implementation period, with coordination indices rising from baseline values of approximately 52% to optimized levels exceeding 82%, as shown in Figure 4(c). Identifying progressive enhancement techniques has provided evidence that a multi-agent system is capable of learning, adapting to changing stakeholder dynamics, and overcoming preservation challenges. Satisfaction assessment shows acceptance of community practitioners and residents across broad demographic categories, with cultural practitioners achieving as high as 94% satisfaction, leading the group, elderly residents achieving 91%, young families achieving 87%, and business owners achieving 85% as shown in Figure 4(d). These findings enable us to conclude that the attempt to strike a balance between the preservation objectives and the community welfare considerations has succeeded, making progress towards long-term sustainability for the initiatives intended for heritage conservation. The analysis regarding long-term sustainability indicates the ability of the framework to endure regarding the maintenance of preservation effectiveness over prolonged time periods while still coping with urban development pressure as shown in Figure 5(a). Historical implementation databases suggest that initial levels of preservation effectiveness rest at 90.2% with projections estimating a gradual drop to 88.5% in the short term and 87.3% for the long-term scenario, which is a good percentage in the model of minimal degradation rates surpassing traditional approaches to preservation. The framework maintains preservation effectiveness under varying environmental conditions, as made clear in Figure 5(b), displaying the framework's resilience, confirming system stability and adaptability assessment, which shows correlation between these metrics across relief scenarios of stress, from low achieving 92% effectiveness to extreme stress conditions, where they maintain at an 83% performance level.

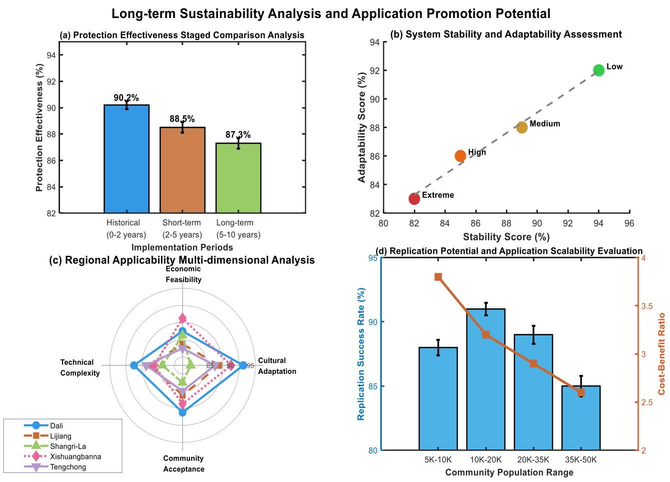

Figure 5. Long-term sustainability analysis and application promotion potential (a) Protection effectiveness staged comparison analysis, (b) System stability and adaptability assessment, (c) Regional applicability multi-dimensional analysis, (d) Replication potential and application scalability evaluation

The applicability assessment at the regional level confirms that the framework can be transferred to other cultural heritage contexts outside the Dali implementation site, as illustrated in the multi-faceted evaluation in Figure 5(c). From the radar diagram, it can be seen that the five regions were evaluated consistently within the same five regional heritage sites. Dali, after all, performed the best on every single measure set forth; whilst Lijiang, Shangri-La, Xishuangbanna, and Tengchong showed applicability potential with varied performance constrained by local contextual factors such as cultural adaptation, economic feasibility, technical complexity, and community acceptance. Deployment considerations include computational infrastructure requirements for handling multi-agent coordination, connectivity challenges in remote heritage sites, and ethical protocols ensuring community participation and data protection. The framework's implementation complexity varies with site scale, with training processes requiring approximately 12.5 hours for system convergence. Replication potential and application scalability evaluation provide evidence of the framework's practical viability for widespread implementation across multiple heritage preservation contexts, as presented in Figure 5(d). The analysis highlights that medium-scale communities with populations between 10,000 and 20,000 have optimal replication success rates of 91%, sustaining acceptable performance levels above 85% across all population categories. The cost-benefit analysis indicates positive economic returns as the ratios decline from 3.8:1 for smaller communities to 2.6:1 for larger implementations, demonstrating economies of scale without negative return profiles. The modular architecture of the framework allows effective adaptation to different cultures while maintaining primary coordination structures, aiding cross-scenario applicability across various ethnic heritage preservation contexts, with demographic and economic development level adaptability showing implementation feasibility.

4. Discussion

The research integrates multi-agent deep reinforcement learning into heritage conservation, marking a systematic application of AI to cultural preservation through architectural innovations that embed cultural values within computational processes. This framework advances beyond passive documentation toward dynamic preservation management, incorporating actionable AI-based coordination that affects outcomes through stakeholder behavioral change. Unlike conventional optimization systems, it unifies collective cultural objectives while balancing competing interests through advanced multi-agent coordination. The design demonstrates responsible AI deployment in culturally sensitive contexts, advancing the discourse on explainable AI and responsible AI [28] by using artificial intelligence to enhance rather than replace human decision-making in heritage management. Framework integration with governmental systems occurs through API interfaces linking heritage databases and permit systems, supported by AI governance committees and standardized protocols. The system enhances policy formulation via predictive analytics and automated compliance monitoring while maintaining human oversight for cultural decisions through legislative frameworks that recognize AI-assisted heritage management.

Recent cultural heritage digitalization studies focus primarily on documentation and visualization rather than dynamic preservation management [29]. This work differs by incorporating actionable coordination approaches affecting preservation outcomes through stakeholder behavioral change. The framework works toward unifying collective cultural objectives and balancing competing stakeholder interests through advanced multi-agent coordination [30], supporting emerging approaches to trust and community control in heritage technology [31]. These findings enable scaled, culturally grounded implementations across diverse contexts. Despite methodological robustness, the framework faces inherent limitations in quantifying cultural identity factors and traditional knowledge systems. Neural network architectures operate within computational bounds that may inadequately capture contextually sensitive decision-making processes. Data availability remains challenging for intangible heritage elements that resist systematic digitization. These constraints highlight the tension between computational efficiency and cultural complexity in heritage preservation systems. Future developments should address deployment constraints through edge computing, hybrid offline systems, and community advisory boards, ensuring ethical oversight. Advanced experience replay mechanisms and explainable AI techniques offer pathways for improving cultural adaptability and decision transparency [32]. Expanding the framework to incorporate metaverse applications and immersive technologies presents opportunities for enhanced community engagement. Critical advances require algorithms distinguishing between adaptive cultural evolution and erosive change, ensuring preservation fosters living heritage rather than a static documentation. These directions emphasize developing computationally efficient yet culturally nuanced representation methods that respect the complexity of heritage systems.

5. Conclusion

This research demonstrates the effectiveness of cultural identity-oriented multi-agent reinforcement learning frameworks in traditional residential heritage preservation, achieving performance metrics that validate the viability of AI-driven approaches in culturally sensitive contexts. The proposed framework attains 89.3% overall accuracy in preservation decision-making, with cultural preservation effectiveness reaching 87.2%, outperforming conventional approaches by 15-25 percentage points across all evaluation metrics. The enhancement mechanism of cultural identity shows improvement, achieving the impact of community cultural attachment and social harmony, yielding outcomes of 91.2% and 86.4% respectively, from the baseline levels of 58.3% and 54.7%. Therefore, these results serve as evidence that intelligent agent coordination balances cultural, community, and stakeholder interests while optimizing value across different scales. The findings combine disciplines of Artificial Intelligence and the processes of cultural heritage protection into one by developing a multi-agent coordination mechanism that addresses conflicts of 'residents vs. experts'. The efficiency rate exceeds 85% across all stakeholder categories, reaching 92% in the resident-expert collaboration. Preservation efforts demonstrate replicable success across various community scales with population sizes between 5,000 and 50,000 residents while sustaining success rates, indicating framework adaptability to numerous contexts of heritage preservation. Economically, the cost-benefit analysis demonstrates the financial viability of AI-based initiatives, with ratios ranging from 2.6:1 to 3.8:1. As for the application of deep learning technology on cultural heritage, AI applications in cultural heritage will expand to include multi-modal decision support systems, which can leverage visual, textual, and spatial cultural data. The foundation of this research allows the integration of large language models and cultural knowledge graphs to construct advanced systems for modelling cultural cognition, capturing intricate relations and transmittal mechanisms of culture. The growing availability of explainable AI methods will improve transparency and openness concerning the use of artificial intelligence in the processes of heritage preservation, making it easier for local people to control the technology designed to help them without losing cultural and traditional governance over the preservation efforts.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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