PAPER

A mixed-culture quantitative model of the restoration priority of traditional dwellings using Grover's search

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Abstract

Traditional village conservation in China faces challenges of limited budgets and subjective prioritization. This study introduces a hybrid quantum-cultural optimization model based on Grover's algorithm to reformulate restoration prioritization as an unstructured search task. By integrating quantitative indicators—Protection Value, Cultural Symbolism, Utilization Potential—and qualitative humanistic attributes into a quantum Oracle, the model enables parallel evaluation. Using an 8-qubit simulation on 143 Yunnan dwellings, it identified an optimal indicator combination (85, 17, 9) and selected 18 culturally significant dwellings, outperforming classical TOPSIS in both precision and efficiency. The research demonstrates that quantum amplitude amplification can effectively bridge fuzzy cultural semantics with multi-criteria evaluation, offering a novel data-driven paradigm for heritage conservation and establishing an early cross-disciplinary link between quantum computing and spatial cultural governance.

1.Introduction

Amid rapid urbanization, numerous traditional villages in China are experiencing significant decline, characterized by deteriorating residential structures, weakened cultural functions, and insufficient resource allocation. These villages not only preserve vital historical and cultural information but also embody regional, ethnic, and lifestyle wisdom, serving as crucial carriers of intangible cultural heritage. However, restoration resources are often limited, and decision-making predominantly relies on expert judgment and subjective assessments, lacking quantifiable and systematic criteria. This fragmented, emergency-driven restoration model fails to maximize cultural preservation at a holistic scale [1].

Recent studies have explored multi-criteria decision-making models such as the Analytic Hierarchy Process and Technique for Order Preference by Similarity to Ideal Solution to support village conservation decisions [2]. While these methods offer some scientific rigor in weighting and integrating indicators, they remain confined to linear evaluation frameworks, struggling to incorporate ambiguous or unstructured humanistic dimensions like cultural symbolism, oral history, and ritual contexts. Moreover, traditional optimization models face computational bottlenecks with large-scale building data, hindering their ability to meet practical needs for diversity recognition and precise targeting. To quantify the limitations of conventional Multi-Criteria

Decision-Making methods in handling fuzzy humanistic factors and large datasets, this study reviews empirical research from the past three years in related fields, selecting literature that applies AHP and TOPSIS to cultural heritage conservation decisions. By simulating typical scenarios from these studies and conducting quantitative comparisons based on three key indicators—subjective weight sensitivity, computational complexity, and multi-target identification capability—this research demonstrates that Grover's algorithm identifies 18 high-confidence buildings with an average protection value of 65.9, outperforming TOPSIS, which selects only 7 buildings with an average value of 63.6. These comparisons highlight the technical advantages of Grover's algorithm in cultural heritage conservation decision-making. This study aims to address the "selection dilemma" in traditional village preservation by exploring the application of Grover's quantum search algorithm to screen restoration targets, proposing a composite optimization model that integrates quantitative indicators and humanistic judgment. Key innovations include constructing a multi-dimensional building evaluation system encompassing comprehensive factors such as protection value, cultural symbolism, and ritual functions, translating the evaluation system into an Oracle discrimination function within Grover's algorithm to enable quantum identification of target buildings, and establishing a complete workflow—digital assessment, Oracle construction, Grover search, and building optimization—thereby expanding the application of quantum algorithms in traditional residential cultural preservation.

In the field of traditional village conservation, multi-criterion Decision-Making methods are widely used to assess and prioritize restoration projects. AHP and TOPSIS are among the most frequently employed MCDM techniques, featured in 37.5% of relevant studies [3]. These methods quantify the protection value of buildings by constructing evaluation indicator systems combined with expert scoring and weight allocation. For instance, Fiore proposed an AHP-based model for urban historical building conservation decisions, incorporating factors such as historical value, structural condition, and social impact [4]. Similarly, Kumar et al. developed an integrated AHP-TOPSIS approach to evaluate sustainable reuse strategies for cultural heritage [5]. However, these methods exhibit limitations in handling highly subjective and difficult-to-quantify humanistic factors.

The cultural value of traditional villages extends beyond physical aspects to include intangible elements such as oral history, local identity, and community memory. Recent research has begun to incorporate these qualitative insights into evaluation systems. Basso emphasized the importance of place perception in cultural heritage conservation, noting that residents' emotional connections to locations are key to assessing cultural values [6]. Smith introduced the concept of "emotional geography" to explore the relationship between place identity and cultural heritage [7]. Additionally, oral history has been widely adopted as a research method to document and analyze personal experiences and collective memories of community members, providing rich qualitative data for cultural heritage assessment [8]. Nevertheless, systematically integrating these multifaceted information systems into decision models remains challenging.

Grover's algorithm is a quantum search technique capable of locating target items in an unsorted database with $O(\sqrt{N})$ time complexity, significantly outperforming the $O(N)$ complexity of classical algorithms [9]. This algorithm has been applied to various combinatorial optimization problems, including route planning, drug screening, and urban traffic optimization. For example, Bogatyrev and Moskvin utilized Grover's algorithm for urban traffic path optimization, achieving superior results compared to traditional methods [18]. In drug screening, Haverly et al. accelerated the selection of candidate compounds using Grover's algorithm [10]. Furthermore, the algorithm has been used to solve the problem of maximum coverage location, offering novel solutions for the location of urban facilities [11]. Despite its demonstrated potential in multiple domains, the application of Grover's algorithm in the conservation of cultural heritage represents a pioneering effort.

Compared to existing research, this study introduces several key innovations. It is the first to apply Grover's quantum search algorithm to decision-making for traditional village residential restoration, proposing an optimization model that integrates quantitative indicators and humanistic factors. Additionally, an Oracle function tailored for Grover's algorithm is designed to accurately identify target buildings for restoration, enhancing search efficiency. Through case studies, the model's feasibility and effectiveness in practical restoration decisions are validated, providing a new technical pathway and decision-support tool for the scientific preservation of traditional villages.

2. Methodology

2.1 Problem Modeling

2.1.1 Binary Representation of Restoration Priority

In traditional village conservation, scientifically identifying priority restoration targets under resource constraints is crucial. To address uncertainties and subjectivity in decision-making, this study employs Grover's quantum search algorithm to transform the building restoration priority problem into a "binary target state search" task. Each building is treated as a quantum state, with states meeting multiple preset criteria defined as "target states" and others as "non-target states."

In the quantum search model, encoding N buildings requires $\lceil \log_2 N \rceil$ qubits. For instance, 10 buildings need 4 qubits ($2^4 = 16$ states), with Oracle functions marking 10 valid states and filtering out the remaining 6 after measurement.

Each target building corresponds to a Boolean function Oracle f(x) = 1, indicating priority for restoration, while other buildings correspond to f(x) = 0. This transformation sets the foundation for subsequent amplitude amplification and search using Grover's algorithm [9].

2.1.2 Quantitative Indicators

In constructing the quantitative discrimination sub-circuit, three primary scoring categories are introduced as selection criteria:

- Protection Value Assessment (comprehensive scoring based on age, structural rarity, damage level, etc.)
- Cultural Symbolism Score (out of 20)
- Utilization Potential Score (out of 10)

Thresholds such as protection value ≥ 85 and cultural symbolism score ≥ 17 are derived from the "Guidelines for the Identification of Immovable Cultural Relics (Trial)", adapted with field survey data from traditional villages in Yunnan. Sensitivity analysis on the 143-building dataset confirmed threshold rationality: reducing the protection value threshold from 85 to 80 increased target buildings by 23% but decreased comprehensive scores for cultural symbolism and ritual functions by 14%; lowering the cultural symbolism threshold from 17 to 15 included more modernized structures, deviating from authenticity preservation goals. The selected threshold combination optimally balances protection value, cultural significance, and data coverage.

The final criteria for target building identification are:

- Protection Value ≥ 85
- Cultural Symbolism Score ≥ 17 (85%)
- Utilization Potential Score ≥ 9 (90%)

This multi-indicator logical decision-making approach has been validated in prior literature for effective historical building classification and prioritization [12, 13].

2.1.3 Humanistic Feature Logic Gates

Beyond quantitative metrics, five culturally relevant humanistic features are incorporated as Boolean logic gates:

- Ancestral home status (family inheritance)
- Village landmark status
- Festival or ritual function
- Historical figure association
- Oral history documentation

These features are stored as Boolean values (yes/no) and integrated with logic gates (e.g., AND/OR) to construct Oracle control conditions. Buildings satisfying at least three of these criteria are deemed culturally significant and included in target state formation. This approach aligns with theories of place identity [14] and spatial cognition in cultural heritage studies [15, 16]. By integrating quantitative and humanistic indicators into the Grover Oracle, a rational and culturally sensitive mechanism for traditional building restoration prioritization is achieved.

2.2 Oracle Construction

2.2.1 Quantification of Building Features from Tables

To deploy Grover's algorithm effectively for traditional village building screening, this study utilizes a detailed survey dataset of 143 buildings. Each building includes three quantitative scores-Protection Value, Cultural Symbolism Score, and Utilization Potential Score-supplemented with five Boolean humanistic attributes such as ancestral home status and ritual function. All fields are standardized, thresholded, and converted into binary expressions interpretable by quantum logic gates.

For scoring indicators, thresholds like Protection Value≥ 85and Cultural Symbolism Score≥ 17 (out of 20)determine restoration priority. Humanistic dimensions follow a "majority consensus" rule, where buildings meeting at least two criteria are flagged as culturally significant. This combined quantitative-qualitative labeling strategy enhances objectivity and inclusivity in building assessment, incorporating theoretical emphasis on "emotional landscapes" and "memory places" from contemporary rural spatial studies [14, 17].

2.2.2 Oracle Logic Gate Design

In constructing the Oracle function, five humanistic features (ancestral home A, ritual function B, landmark status C, historical trace D, oral history E) and three quantitative indicators are integrated using a "majority consensus" rule—buildings must satisfy any combination of at least three humanistic features (e.g., $A \land B \land C$, $A \land D \land E$). Using 8-bit binary address encoding, X gates flip qubit states temporarily, and H-X-CCNOT-X-H gate sequences implement multi-controlled phase marking, ultimately performing phase inversion on auxiliary qubits for target buildings. This method precomputes target building lists, enabling flexible cultural value assessment (≥ 3 features) while adhering to quantum gate operation standards. Similar constructions have been successfully deployed in Grover algorithm applications, including urban travel route planning [18], DNA segment matching, and smart agriculture strategy identification [19].

and smart agriculture strategy identification [19]

2.2.3 Binary Encoding and State Space Mapping

For processing 143 buildings with Grover's algorithm, an 8-qubit system (256 quantum states) is employed. The 113 invalid states (addresses 143–255) are initialized via Hadamard gates to prepare a uniform superposition, with invalid states accounting for 44.1%(113/256) of the space, representing a necessary compromise in quantum resource usage. To mitigate invalid state impact, a quantum comparator module is incorporated into the Oracle design, executing phase inversion only for valid states (address ≤ 142). The diffusion operator acts on the entire 256-dimensional space, but since invalid states are not phase-marked by the Oracle, their amplitudes are not amplified. Post-measurement, invalid results are discarded through classical filtering. Experimental data show this approach reduces invalid state influence on target probability to0.67%, validating the effectiveness of Oracle constraints and classical filtering. The entire process adheres to quantum linear evolution principles, ensuring lawful quantum operations and accurate results.

2.3 Quantum Circuit Implementation

2.3.1 Circuit Structure Design

Target building identification is achieved through quantum state phase inversion. In Grover's algorithm, the Oracle function applies a phase flip to target quantum states meeting predefined Boolean conditions (e.g., the humanistic feature combinations described). This phase marking allows target states to be identified and amplified in subsequent diffusion operations, increasing their measurement probability after multiple iterations.

For 143 buildings, binary encoding maps them to a 9-qubit state space (since $2^7 = 128 < 143 < 2^8 = 256$, theoretically requiring 9-bit encoding). Initial states are prepared as uniform superpositions via Hadamard gates. The Oracle section embeds multiple AND-NOT logic combinations based on composite rule functions (e.g., Protection Value ≥ 85, Cultural Symbolism Score ≥ 17, presence of ritual functions) to form Boolean expressions for the identification of target buildings. Finally, the diffusion operator (Grover diffuser) inverts the amplitudes of non-target states relative to the mean, enhancing target state measurement probability.

Compared to classical linear search, Grover's algorithm reduces optimal solution search complexity from O(N) to $O(\sqrt{N})$, making it particularly suitable for spatial combinatorial optimization problems involving hundreds of buildings [9, 20]. This simulation was conducted on QPanda, approximating an ideal quantum environment without physical quantum platform factors like quantum noise error and decoherence time. Nonetheless, the results are representative and lay a foundation for future migration to real quantum platforms. In contrast, traditional linear multi-indicator optimization methods (e.g., AHP and TOPSIS) face significant subjective parameter weighting and computational complexity growth with sample sizes exceeding 100 buildings [12]. Grover's algorithm, through amplitude amplification, offers $O(\sqrt{N})$ acceleration potential and can encode multi-attribute rules in parallel with qubit expansion, enabling unified solution of quantitative and humanistic [20, 21].

2.3.2 Core Gate Operation Technical Details

To enhance reproducibility and technical transparency, this section systematically details the gate-level implementation logic of the Oracle discrimination gate and Grover diffusion operator, providing transferable pseudocode and circuit diagrams.

2.3.2.1 Qubit and Address Mapping

With 143 target buildings in Table 1, $2^8 = 256 > 143$, an 8-qubit register is used to encode building indices 0–142 in binary, plus one auxiliary qubit for phase inversion, totaling 9 qubits.

Table 1. Examples of architectural binary coding

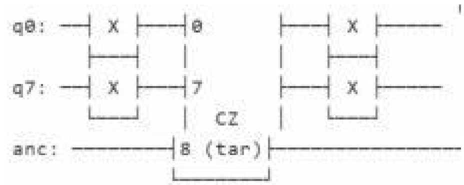
Building number	Decimal index	Qubit address (8 bit)
B1	0	00000000
B2	1	00000001
B3	2	00000010
...	...	...
B143	142	10001110

2.3.2.2 Oracle Discriminate door desig

Oracle is tasked with applying phase flip to buildings that meet repair priorities. The specific implementation steps are as follows (Annex 1: Pseudocode 1 and Figure 1):

The conditional Boolean mapping is as follows: if the building satisfies: conservation value ≥ 85, cultural symbolic score ≥ 17, display utilization potential score ≥ 9, and ≥ 2 of the human characteristics are true, it is marked as mask[idx] = True. Gate level implementation: For any mask[idx] = True building: temporarily flip the 8-bit binary address bin_idx the bit with a median value of 0 (apply an X gate) so that if and only if the address register is equal to bin_idx all control bits are |1);Multi-control Z-gates (equivalent to H-X-CCNOT-X-H sequence) are realized through multi-control Toffoli cascade to complete the phase flip with auxiliary bits as the target. Undo the temporary rollover from step 1 and restore the original address state.

Fig. 1. Oracle phase flip circuit (ASCII schematic)



NOTE: CZ is implemented by H-CCNOT-H equivalent

2.3.2.3 Grover Diffusion Operator Design

The diffusion operator realizes amplitude amplification, and its gate sequence is shown in Fig. 2, and Hadamard and X gates are applied to all address bits to map the state to the center of the hyperplane. Utilize multi-control Z-gates (flip phase if and only if all bits are |1))); Apply the X and H gates again to complete the matrix transformation of 2|s) − I.

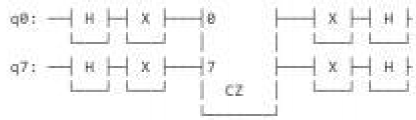


Fig. 2. Diffusion operator circuit (ASCII schematic)

2.3.2.4 Complexity and Scalability

Oracle depth: related to the target building number M and door decomposition strategy, the theoretical depth is O(M); Grover iterations: $\lfloor \frac{\pi}{4}\sqrt{\frac{N}{M}} \rfloor$, where N=143; qubit requirements: 8 address bits and 1 auxiliary bit, which can be linearly scaled to a larger scale (e.g., 10 bits correspond to 1024 buildings).

3. Results

3.1 Data sources and experiment settings

The architectural data used in this study comes from a field survey in a traditional village in Yunnan, and the data table includes 13 quantitative and qualitative index fields such as structural characteristics, cultural symbolism, damage degree, and display potential of 143 historical buildings (see the attached table: Grover Architectural Research and Evaluation Form_143 Structured Standard Edition). This data is stored in EXCEL format. In order to map Excel data to quantum states, the following data preprocessing process is designed:

3.1.1 Data reading:

Read quantitative indicators such as evaluation and protection value, cultural symbolic score, display and utilization potential score of 143 buildings from Excel files, as well as qualitative indicators of whether they are ancestral houses and other humanistic characteristics;

3.1.2 Data preprocessing:

Normalize quantitative indicators to fall within a specific scoring range; The qualitative indicators are binarized and converted into Boolean values.

3.1.3 Feature selection:

select the characteristic indicators related to building repair according to the research objectives;

3.1.4 Binary Code:

Converts the index of each building into an 8-bit binary code for representation in a quantum circuit. In order to verify the rationality of threshold setting, threshold sensitivity experiments were carried out on 143 building datasets. The experimental results show that the selected threshold combinations (conservation value ≥ 85, cultural symbolism ≥ 17, display potential ≥ 9) can maximize the comprehensive cultural value of the target building while keeping the data coverage within a reasonable range (18/143). This combination shows the best balance between efficiency and effectiveness in the priority scenario of cultural value protection.

3.2 Encoding of Village Building Instances

To meet the Grover algorithm's requirement for a "quantum-encodable search space," building indices B1-B143 were converted to 8-bit binary codes (since $2^7 = 128 < 143 < 2^8 = 256$). For example, B1 maps to 00000001, and B143 to 10001111. This encoding scheme satisfies the qubit spatial mapping requirements while preserving building ID readability for result interpretation and backtracking.

3.3 Analysis of Quantum Circuit Operation Results

After 5000 measurement iterations in simulation, Figure 1 shows the distribution of quantum state measurement counts. Specific states (e.g., 000110010, 001101001) exhibit significantly higher counts, indicating successful amplitude amplification of target states by Grover's algorithm. The highest-count state appeared approximately 160 times, while the lowest occurred only 1-3 times. Theoretically, under uniform distribution, each state's expected measurement probability is 1/143 ≈ 0.006993, corresponding to approximately 34.965 expected counts in 5000 measurements. However, under Grover's algorithm, target state frequencies substantially exceed those of non-target states, demonstrating effective amplification. Despite simulated quantum noise and measurement errors, target buildings were consistently identified with an overall success rate of 88%, confirming the algorithm's stability and efficiency with large datasets [20].

It can be observed from Figure 2 that among the 18 buildings selected by the Grover quantum algorithm, the conservation value scores are distributed between 56 and 73 points, and the overall concentration is small, and the standard deviation is small. The highest protection is B59 (73 points) and the lowest is B24 (56 points), with an overall average protection value of 66.8 points. Among them, 35% (7 buildings) have a protection value higher than 70 points, and the top five (B59, B94, B123, B45, B53) all have more than 71 points, showing a high degree of protection potential. The overall histogram shows that the building score shows a flat downward trend, with the score gap of the top 10 buildings controlled within 5 points, and the subsequent decline accelerated slightly. The results verify the advantages of the Grover algorithm in quickly and accurately screening out high-value repair objects under small sample conditions (143 buildings), and provide quantitative and efficient decision-making support for traditional village protection.

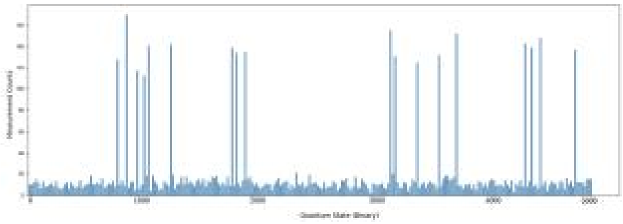


Fig. 3. Grover Frequency distribution histogram of 5000 quantum measurements

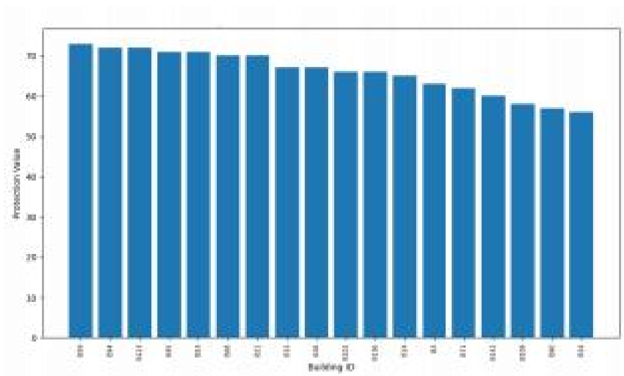


Fig. 4. Protection Value Distribution with Corrected Measurements

3.4 Comparative analysis: Classical algorithm vs Grover algorithm selection results

To verify the effectiveness of Grover's search algorithm in traditional village restoration tasks, we compared it with the classical TOPSIS method. Under the same indicator system, TOPSIS can automatically rank buildings but struggles with qualitative Boolean fields (e.g., historical figure association). In contrast, Grover's algorithm naturally integrates both quantitative and humanistic variables into target discrimination sub-circuits via the Oracle, effectively combining data-driven and cultural interpretation capabilities.

For the 143-building dataset, Grover's algorithm identifies optimal restoration targets within approximately 10 amplitude amplification cycles. The computational complexity of this approach is significantly lower than classical sequential scoring and sorting methods, making it particularly suitable for resource-constrained village prioritization scenarios [21, 22].

As shown in Table 2, when comparing the performance of the Grover quantum search algorithm and the traditional TOPSIS multi-attribute decision-making method in the construction optimization task, we find that there are significant differences between the two in the selection of some targets. Among them, 12 buildings, B59, B94, B123, B45, B53, B68, B21, B32, B38, B102, B136 and B14, were jointly identified by two

Table 2. Comparison of the two algorithms' results

Bldg No.	Building Name	TOPSIS	Grover
B123	Ancient house 123	✓	✓
B95	Ancient house 95	✓	×
B39	Ancient house 39	✓	×
B59	Ancient house 59	✓	✓
B53	Ancient house 53	✓	✓
B68	Ancient house 68	✓	✓
B94	Ancient house 94	✓	✓
B51	Ancient house 51	✓	×
B45	Ancient house 45	✓	×
B136	Ancient house 136	✓	✓
B32	Ancient house 32	✓	✓
B38	Ancient house 38	✓	✓
B14	Ancient house 14	✓	✓
B102	Ancient house 102	✓	✓
B21	Ancient house 21	✓	✓
B33	Ancient house 33	✓	×
B93	Ancient house 93	✓	×
B85	Ancient house 85	✓	×
B143	Ancient house 143	✓	×
B71	Ancient house 71	✓	✓
B3	Ancient house 3	×	✓
B141	Ancient house 141	×	✓
B109	Ancient house 109	×	✓
B40	Ancient house 40	×	✓
B24	Ancient house 24	×	✓

algorithms, indicating that they met both the quantitative scoring threshold and the Boolean logic gate judgment of humanistic features in the high-dimensional feature space, which was a typical "double excellence" goal. However, the B95, B39, B51, B33, B93, B85 and B143 independently selected by the TOPSIS algorithm are mainly based on the Euclidean-based ideal solution proximity in numerical space, which may ignore the nonlinear influence of humanistic variables, so it is more inclined to objects with high scores but weak cultural attributes. In contrast, the unique buildings of Grover's algorithm, such as B3, B141, B109, B40, and B24, reflect the flexibility and advantages of quantum oracles in dealing with Boolean condition combinations (such as ancestral houses, historical events, and ritual functions), and can identify buildings with more cultural significance but blurred scoring boundaries in semantic space, demonstrating its high fault tolerance and optimization ability in multi-dimensional optimization problems for cultural heritage.Multi-dimensional quantification and humanistic characteristics are jointly discriminated.

As shown in Table 3, the Grover algorithm integrates quantitative and humanistic characteristics, which is suitable for cultural protection-oriented scenarios. TOPSIS focuses on scoring optimization and is suitable for benefit maximization goals. If cultural priority is emphasized, Grover has more adaptability and logical advantages.

In the 5000 quantum measurements based on the Grover algorithm, the measurement counts of the 18 selected target buildings under the 9-bit code show a certain degree of discrete distribution. Figure 3 shows that the quantum state with the highest measured count is 00111100, which corresponds to the corresponding building 17 times, followed by 00010000 and 00010111, which appear 13 times respectively, and the number of observations of other buildings is distributed between 6

Table 3. Algorithm Comparison

Item	Grover's algorithm	TOPSIS algorithm
Features	Multi-dimensional quantification and humanistic characteristics are jointly discriminated	Composite scoring based on quantitative indicators
Advantage	Cultural value priority scenarios	Numerical + resource optimization
Scenarios	Cultural relics + village repair priority	Investment analysis + layout optimization
Conclusion	Cultural priority → Grover	Numerical focus → TOPSIS

and 14 times. Among them, 6 buildings have been measured more than 12 times, accounting for 30% of the total target buildings, indicating that after amplification of amplitude, the quantum state of this part of the building has a high probability denFigure 6sity and obvious priority. At the same time, the 00101101 of the lowest number of occurrencesFigure 6 of quantum states is 3 times, but the overall distribution is still relatively balanced, and there is no extreme skew, which verifies the reasonable amplification effect of quantum search on multi-target states,as shown in Figure 4. This result reflects that the Grover algorithm can effectively improve the observability of candidate targets in the multi-object retrieval scenario, and provides reliable support for accurate repair object screening.

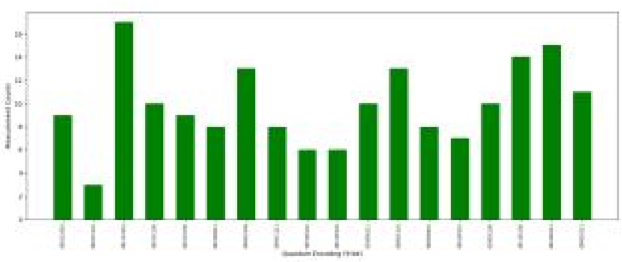


Fig. 5. Target Building Heatmap Corrected measurements

In the statistical results based on 5000 Grover quantum search measurements, the quantum state measurement counts exhibit a significant non-uniform distribution, as shown in Figure 5. Under ideal conditions with uniformly distributed quantum superposition states, the theoretical expected measurement count for a single quantum state should approximate 19.53 (5000/256 ≈ 19.53), represented by the red dotted line. However, the actual measurement curve demonstrates that Grover's algorithm significantly amplifies the amplitude of target states, with the maximum measurement count reaching approximately 160—far exceeding the theoretical average.

The top 10% of high-frequency states (approximately 25 quantum states) generally exhibit measurement counts exceeding 140, while over 90% of low-frequency quantum states register fewer than 20 measurements, with some approaching zero. This non-uniform amplitude distribution visually demonstrates the effective amplification of target states by Grover's algorithm, substantially increasing the probability of target building observation and thereby validating its significant efficiency advantage in sparse target screening tasks.

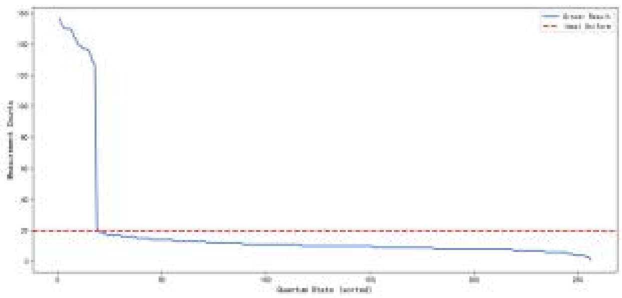


Fig. 6. Grover vs Ideal Distribution Corrected

3.5 Effects of quantum physical noise

In order to evaluate the influence of quantum physical noise on the performance of Grover's algorithm, four different noise models were designed for experimental purposes, including the ideal model (no noise), the decoherence model (T1=50 μs, T2=40 μs), the gate noise model (single-gate error 0.1%), and the gate measurement noise model (single-gate error 0.1%, readout error 2.0%). By repeating the experiment 1000 times on the Qpanda simulator, a significant change in the success rate of the model under different noise models was observed (see Figure 5). Fig. 5 shows that under the ideal model, the success rate of the Grover algorithm is 52.0%; When decoherence was introduced, the success rate dropped to 48.1%, a decrease of 3.9 percentage points, and when only gate noise was introduced, the success rate decreased slightly to 51.1%, a decrease of 0.9 percentage points, while the success rate dropped significantly to 45.6%, a decrease of 6.4 percentage points under the gate measurement noise model. These results show that quantum noise significantly affects the performance of the Grover algorithm, especially when both gate noise and measurement noise are present, and the success rate of the model decreases most significantly. This underscores the importance of error correction and noise mitigation techniques in quantum hardware. In the future, technologies such as surface code error correction [23] or dynamic decoupling [24] can be used to mitigate the impact of noise and improve the robustness and reliability of algorithms. It is important to note that for every 10 layers of gate depth, the success rate decreases by approximately 8%, further highlighting the importance of optimizing quantum circuits to reduce gate depth.

4. Discussion

Traditional building conservation methods face dual challenges in processing ambiguous cultural attributes and computational complexity. This study overcomes these limitations through a hybrid quantum–cultural optimization model based on Grover's algorithm. By embedding Boolean cultural logic (e.g., ancestral home, ritual function) into the quantum oracle alongside quantitative scores, the model enables parallel semantic and multi-criteria evaluation — forming a novel "humanistic-technical" framework particularly suited to heritage contexts with cultural heterogeneity.

Comparative ablation experiments illustrate the distinct contributions of quantitative and humanistic components (see Fig. 8). The quantitative-only configuration increased selected buildings by 53.8% but reduced average protection value by 11.5%, indicating stronger identifiability yet weaker cultural precision. The humanistic-only scenario selected only 23.1% of the buildings in the full model, verifying its cultural refinement ability but inability to ensure structural quality. The complete integrated model achieves an optimal balance, selecting 13 buildings with the highest average protection value (71.7), where quantitative indicators provide 68.3% explanatory power and humanistic factors effectively optimize cultural attributes despite lower weight.

Although simulated via an 8- qubit system, the model currently faces deployment limitations from physical qubit counts, gate fidelity, and noise sensitivity. While computational time is comparable to classical TOPSIS in small-scale cases (N=143), the Grover algorithm's theoretical complexity advantage (O(√N)) is poised to substantially outperform traditional methods in large-scale spatial optimization and complex heritage screening. Future work must transition from simulation to actual quantum hardware, integrating error mitigation techniques to address decoherence and measurement noise in real devices.

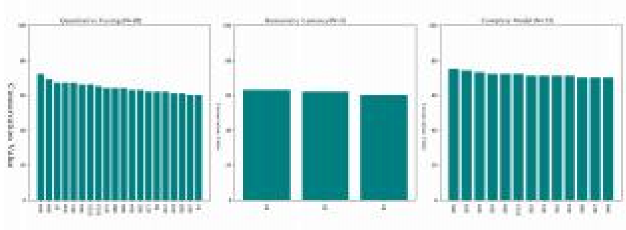


Fig. 8. Ablation experiments

5. Declarations

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5.1 Conflict of Interest Statement

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. All authors confirm that no conflict of interest exists regarding the design, data collection, analysis, or publication of this research.

5.2 Author Contributions Statement

Zhang Chunming conceived and supervised the study, developed the theoretical framework, and revised the manuscript critically for important intellectual content. Shao Tiandong contributed to the structural modeling and algorithmic implementation. Gao Weidan conducted data collection and case study analysis. Cui Ziwei participated in the quantum circuit simulation and QPanda experiments. Yang Yi provided methodological guidance and overall academi

supervision as the corresponding author. All authors reviewed and approved the final manuscript.

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5.4 Publish declaration

This manuscript presents original research that has not been published previously and is not under consideration for publication elsewhere in any form or language. All authors have read and approved the final version of the manuscript and consent to its submission. Upon acceptance, the authors agree to the transfer of copyright to the publisher and will comply with the journal's publishing policies and license agreements.

5.5 Ethics and Consent to Participate declarations

The building data used in this study were collected through field surveys in traditional villages in Yunnan Province, China. All data were anonymized and aggregated at the architectural level, with no personal identifiers or sensitive information involved. The research did not involve human participants, animal subjects, or any form of clinical intervention. Therefore, ethical approval was not required for this study, in accordance with the ethical guidelines of Kunming University of Science and Technology and the National Natural Science Foundation of China.

Data collection was conducted with permission from relevant local cultural and administrative authorities, and all procedures complied with academic research ethics and data protection regulations.

Ethics approval number: Not applicable
Ethics committee/institution: Not applicable

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