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AI-Driven Narrative Structure Generation and Visitor Path Optimization in Museums

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Abstract. Museum digital transformation is shifting exhibitions from static display toward data-driven cultural experience design. However, many intelligent guide systems still emphasize retrieval, navigation, and efficiency rather than narrative relationships, aesthetic rhythm, and visitor understanding. This study proposes an AI-driven framework for narrative generation and visitor path optimization using open collection metadata, gallery spatial graphs, and simulated visitor behavior. Collection records from 2020 to 2025 are gathered from Smithsonian Open Access, Cleveland Museum of Art, Europeana, and Tate. Knowledge graphs, BERT-based semantic encoding, and large language models are used to generate cultural narrative chains, while Dijkstra's algorithm and NSGA-II optimize visitor routes. Results show that the AI Curatorial Constraint strategy outperforms chronological and semantic-clustering approaches in thematic coverage, coherence, and curatorial consistency. Narrative-optimized routes also improve continuity and reduce congestion while maintaining low movement cost. The framework supports intelligent curation, cultural communication, and public aesthetic education.

Keywords: AI curation, narrative structure generation, visitor path optimization, museum experience, aesthetic education

1. Introduction

Digital technologies are reshaping the way museums organize knowledge, and the relationship among objects, space, and visitors is moving from static viewing toward dynamic interaction. Existing smart museum practices mainly focus on digital guides, virtual displays, and personalized recommendation, which improve access to information, yet they often compress museum experience into route selection and object retrieval, leaving cultural narrative, emotional progression, and aesthetic education insufficiently transformed into computable design elements [1]. In the contexts of cultural and creative industries, museums carry multiple functions, including public cultural communication, urban cultural branding, and the guidance of art consumption, so the use of AI should move beyond service efficiency and participate in meaning-making, knowledge connection, and visitor understanding [2]. AI-driven narrative structure generation and visitor path optimization can draw on open collection metadata, gallery spatial graphs, and simulated visitor behavior data to build an integrated framework linking curatorial logic, algorithmic models, and aesthetic experience,

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thereby examining how technology may support more coherent, culturally interpretable, and educationally meaningful museum visits.

2. Literature review

2.1. Curatorial narrative generation

Curatorial narrative treats exhibitions as spatial forms of knowledge in which object meaning emerges from relations among themes, periods, materials, regions, figures, and social contexts. While traditional exhibitions follow linear historical narratives, digital curation enables multiple interpretive paths, turning fixed narratives into reconfigurable cultural networks [3].

AI models can identify semantic links among titles, tags, descriptions, and image captions to support thematic clustering and storyline construction. However, curatorial narratives cannot rely on semantic similarity alone; historical context, curatorial rules, and value judgments must remain embedded as constraints [4]. AI is therefore better positioned as an interpretive tool that expands connections among objects while preserving curatorial responsibility for cultural memory, aesthetic judgment, and public education.

2.2. Intelligent guide technology

The development of intelligent guide technology allows museums to identify visitor movement trajectories, dwell time, interest preferences, and spatial congestion in more detailed ways. Indoor positioning, QR-code guides, mobile recommendation, and interactive screens provide a data foundation for visitor path optimization, while also transforming exhibition space from a fixed route into a perceptive, adjustable, and feedback-based service system [5]. These technologies are effective in improving circulation efficiency and personalized recommendation, but when route planning is organized only around shortest distance, popular objects, and dwell efficiency, visitors may gain a more convenient experience while failing to develop complete thematic understanding and aesthetic immersion. Intelligent guide design for museum curation needs to transform spatial movement into narrative progression, so that route selection responds to object relations, emotional rhythm, visitor cognitive load, and fairness in public cultural services [6]. Visitor path optimization is therefore not only a traffic problem, but also a question of how exhibitions arrange viewing sequence, cultural interpretation, and aesthetic pause.

2.3. Cultural experience evaluation

Museum experience evaluation has gradually expanded from satisfaction and service quality to cultural understanding, emotional resonance, identity recognition, and aesthetic education. Cultural industry research emphasizes visitor participation and content transformation, while art market and gallery studies focus on viewing behavior, value perception, and aesthetic preference, so museum evaluation needs to address the tension between public educational goals and cultural consumption logics [7]. Narratives and routes generated by AI systems can be assessed through algorithmic indicators such as thematic coverage, semantic coherence, average walking distance, and exposure time at congested nodes, while their cultural effectiveness should also be examined through expert ratings, visitor comprehension tests, emotional feedback, and aesthetic experience scales [8]. When technical and humanistic indicators are placed within the same evaluation framework, museum digitalization can shift from functional optimization to meaning optimization. The evaluation

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process also needs to consider algorithmic bias, cultural labeling, and the distribution of interpretive authority, as these issues affect visitors' access to diverse cultural content and the credibility of museums as public knowledge institutions [9].

3. Experimental methods

3.1. Data sources

Data collection is organized around three levels: collection semantics, gallery space, and visitor behavior. Collection data are obtained from open platforms such as Smithsonian Open Access, Cleveland Museum of Art Open Access, Europeana, and Tate Collection. The year range is limited to publicly accessible open records from 2020 to 2025. The selected fields include object title, creator, period, material, category, thematic tags, description text, and image URL. To ensure computational usability, records with missing core fields, duplicate entries, and description texts of fewer than 30 words are removed. About 1,200 art object and cultural object records with complete metadata are retained. Spatial data are abstracted from public gallery floor plans into a gallery graph. Exhibits, gallery entrances, and transition nodes are defined as nodes. Corridor distance and spatial connections are defined as edges. Visitor behavior data are not claimed as real field survey data. Instead, simulated trajectories are constructed according to parameters from public visitor flow studies, including dwell time, interest themes, movement sequence, and congestion exposure time. This data structure first supports narrative relation modeling in 3.2. It then serves as the spatial and behavioral input for path optimization in 3.3.

3.2. Narrative generation model

Narrative generation first converts each collection object into a semantic vector. The vector input is formed by combining the title, thematic tags, period, material, and description text. A BERT based encoder is then used to obtain the object representation [10]. Cultural association between objects is not judged by a single keyword. Instead, semantic similarity is calculated to form the initial relation edge, as shown in Formula 1.

$$S_{ij}=\cos(e_i,e_j)=\frac{e_i^T e_j}{\|e_i\|\|e_j\|} \tag{1}$$

Here, S_{ij} represents the semantic association strength between object i and object j. e_i and e_j represent the semantic vectors of the two objects. A higher value indicates closer similarity in theme, material, or cultural context. On this basis, the knowledge graph transforms relations such as period, material, theme, region, and creator into constraints. As a result, the language model does not only pursue textual coherence during narrative generation. It also follows curatorial logic. The generation probability of the narrative sequence is shown in Formula 2.

$$P(Y|X,G,C)=\prod_{t=1}^{T} P(y_t|y_{<t},X,G,C) \tag{2}$$

Here, Y represents the generated narrative text sequence. X represents the collection metadata input. G represents the collection knowledge graph. C represents curatorial constraints. y_t represents the generated token at time step ttt. The narrative units produced by this model are further used as the narrative continuity indicator in the path optimization process in 3.3.

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3.3. Path optimization algorithm

Path optimization transforms the museum visit process into a weighted graph search problem. Exhibits and gallery zones are defined as nodes. Corridors, visual transitions, and thematic connections between nodes are defined as edges. The edge weight does not only represent spatial distance. It also includes transition cost, congestion risk, and narrative association [11]. In this way, path planning can follow the cultural narrative structure generated in 3.2. The composite weight of a single edge is shown in Formula 3.

$$w_{ij}=\alpha d_{ij}+\beta q_{ij}+\gamma r_{ij}-\delta S_{ij} \tag{3}$$

Here, w_{ij} represents the composite transition cost from node i to node j. d_{ij} represents standardized distance. q_{ij} represents transition complexity. r_{ij} represents congestion risk. S_{ij} represents narrative association strength. $\alpha,\beta,\gamma,\delta$ are weight coefficients. Dijkstra's algorithm is used to form the shortest path baseline. NSGA II is then used for multi objective optimization. The objective function is shown in Formula 4.

$$\min F(R)=\left(\sum_{(i,j)\in R} w_{ij},-\frac{1}{m-1}\sum_{k=1}^{m-1} S_{v_k v_{k+1}},\sum_{v_i\in R}\rho_i\tau_i\right) \tag{4}$$

Here, R represents a candidate visitor path. m represents the number of path nodes. v_k represents the k_{th} visited node. ρ_i represents node congestion density. τ_i represents the preset dwell time. The first objective controls the composite movement cost. The second objective improves narrative continuity between adjacent exhibits. The third objective reduces congestion exposure.

4. Results

4.1. Narrative quality results

The narrative quality results are obtained from 1,200 open collection records, 5 thematic gallery zones, and 10 random split validations. Three strategies are compared: Chronological Baseline, Semantic Clustering, and AI Curatorial Constraint. The evaluation indicators include thematic coverage, semantic coherence, curatorial consistency, and narrative diversity. All indicators are standardized to a 0 to 1 scale and reported as mean plus standard deviation. As shown in Table 1, Chronological Baseline is stable in chronological order, but its thematic coverage is only 0.614±0.036. This indicates that a purely time based arrangement has limited ability to reveal cross media and cross regional cultural associations. Semantic Clustering increases thematic coverage to 0.721±0.033, but its curatorial consistency is 0.684±0.041. This shows that semantic clustering alone may place objects with similar cultural contexts but different historical logics into the same narrative chain. AI Curatorial Constraint achieves a thematic coverage of 0.786±0.029, a semantic coherence of 0.752±0.034, and a curatorial consistency of 0.811±0.026. This indicates that knowledge graph constraints can reduce contextual jumps in automatically generated narratives. They also make object relations more consistent with curatorial logic and aesthetic education guidance.

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Table 1. Comparison of narrative generation quality

Narrative Strategy	Thematic Coverage	Semantic Coherence	Curatorial Consistency	Narrative Diversity
Chronological Baseline	0.614±0.036	0.603±0.042	0.742±0.031	0.518±0.047
Semantic Clustering	0.721±0.033	0.704±0.038	0.684±0.041	0.673±0.035
AI Curatorial Constraint	0.786±0.029	0.752±0.034	0.811±0.026	0.706±0.032

4.2. Visitor path results

Path optimization is tested on a simulated gallery graph containing 68 exhibit nodes, 12 transition nodes, 91 edges, and 120 candidate paths. Fixed, shortest-distance, and narrative-optimized routes are compared. The fixed route shows a movement cost of 0.684±0.071, narrative continuity of 0.612±0.048, and congestion exposure of 0.431±0.052. The shortest route reduces movement cost to 0.496±0.058 but lowers narrative continuity to 0.547±0.055.

The narrative-optimized route achieves a balanced result, with movement cost of 0.538±0.049, narrative continuity of 0.734±0.043, and congestion exposure of 0.287±0.041. As shown in Figure 1, Pareto-optimal routes concentrate around lower movement cost and higher narrative continuity, while smaller points indicate reduced congestion. The results confirm that optimization jointly considers narrative progression, spatial comfort, and visiting efficiency rather than distance alone.

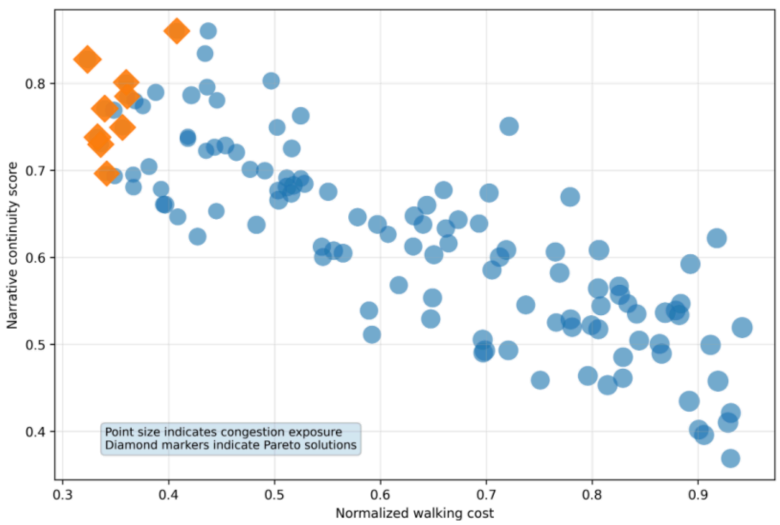

Figure 1. Pareto distribution of multi objective visitor path optimization

5. Discussion

The experimental results show that the value of AI-assisted curation is not limited to text generation or route shortening. Its deeper role lies in integrating object semantics, spatial structure, and visitor behavior into a computable narrative system. The AI Curatorial Constraint strategy reaches 0.811±0.026 in curatorial consistency. This indicates that knowledge graph constraints can reduce historical context breaks often found in semantic clustering, making generated narratives closer to

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curatorial logic. At the same time, the narrative-optimized route has a slightly higher movement cost than the shortest-distance route, but its narrative continuity increases to 0.734±0.043. This suggests that museum path design should not only pursue spatial efficiency. A moderate increase in movement cost can support a more complete thematic progression and a more stable aesthetic rhythm. The congestion exposure value decreases to 0.287±0.041, showing that multi-objective optimization can also improve spatial comfort. Therefore, the key role of computational models in museum contexts is to place efficiency, cultural interpretation, and aesthetic education within the same design logic.

6. Conclusion

AI-driven narrative structure generation and visitor path optimization provide a feasible framework for connecting computational methods with museum curation. Open collection metadata, gallery spatial graphs, and simulated visitor behavior data support a reproducible experimental process. Semantic encoding, knowledge graphs, large language models, and multi-objective optimization jointly identify cultural associations, generate curatorial narratives, and improve visitor routes. The results show that curatorial constraints enhance thematic coverage, semantic coherence, and narrative consistency, while narrative-optimized routes balance movement cost, spatial comfort, and aesthetic experience. This framework offers methodological support for intelligent museum guides, digital curation, cultural communication, and public aesthetic education. Future research can further test the model through real museum settings, visitor feedback, and cross-cultural exhibition cases.

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