

Visual Representation of "Chinoiserie" in Western AI Image Models: A Case Study of Midjourney

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Abstract

Using visual grammar as its theoretical framework, this study adopts a comparative experimental approach to perform a multimodal discourse analysis on 240 "Chinoiserie" (Chinese style) images generated by Midjourney. The analysis evaluates baseline and professionally constrained prompt groups across three dimensions: architectural space, costumed portraiture, and landscape atmosphere. Results show that in representational meaning, the model exhibits attribute ambiguity, structural dislocation, and cultural semantic rupture, achieving high adaptability only with abstract landscape styles. In interactive meaning, it demonstrates a spectacularized and Othered perspective, constructing a Eurocentric narrative through low-angle shots and demand-gaze interaction. In compositional meaning, stereotypical symbols occupy an exceptionally high proportion; professional constraints paradoxically exacerbate symbol stacking, and the aesthetic of negative space (Liu Bai) is entirely erased during entity generation. The study indicates that the "Chinoiserie" generated by Western AI is not an authentic cultural representation but a de-historicized digital simulacrum marked by significant cultural bias and aesthetic homogenization. Finally, governance recommendations regarding dataset construction and prompt optimization are proposed to serve as empirical references for the cross-cultural communication of Chinese culture and algorithmic bias correction in the AI context.

Keywords

AI-Generated Imagery; Chinoiserie; Cultural Bias

1. Introduction

With the continuous upgrading of generative artificial intelligence (AIGC) technology, text-to-image models have gradually become important media for cultural dissemination in the digital era. Leveraging high productivity and diverse visual expressions, AI-generated imagery has increasingly penetrated fields such as design, journalism, and creative industries, reshaping the production and dissemination of traditional visual culture works. Serving as a "mirror" of humanity,

AI exerts a dual effect in reshaping media structures and social contexts during the dissemination of traditional culture. As a visual symbolic system carrying the core of traditional Chinese culture, "Chinoiserie" encompasses landscape atmosphere, traditional architecture, Hanfu aesthetics, and folklore symbols. It acts as both a core symbol of Chinese culture's global communication and an important medium for cross-cultural visual exchange. In recent years, "Chinoiserie" has achieved wide global recognition through media such as "Li Ziqi," the domestic video game *Black Myth: Wukong*, New Chinese-Style clothing (Horse-face skirts), and the animated film *Ne Zha 2*. In March 2024, UNESCO published a research report pointing out that large language models exhibit tendencies such as gender bias and racial stereotyping, calling on governments to establish regulatory frameworks (UNESCO, 2024). This warning applies equally to text-to-image models—research shows that such models also demonstrate systematic bias when generating images of non-Western cultures. Using AI foundation models to reconstruct the real world, these cultural works become products encoded, reorganized, and represented by algorithms based on training data. Their visual representations and cultural connotations are deeply affected by algorithmic logic and data sources, which can influence users' cognition of both the real world and virtual space during dissemination. As AIGC technology impacts global cultural dissemination, "Chinoiserie" as a cultural symbol faces crises of algorithmic reconstruction and stereotyping.

According to the 2025 Artificial Intelligence Index Report released by Stanford University's Stanford Institute for Human-Centered Artificial Intelligence (HAI), the United States maintains its leading position in the research and development of top-tier AI models, consistently producing more significant machine learning models over the past decade than any other country. Generative AI represented by text-to-image models such as Midjourney and DALL-E 2 inevitably presents Western mainstream values alongside certain cultural biases and ideological tendencies. This reflects real-world issues in human-computer interaction, such as uneven capital accumulation, global cultural power imbalances, and a communication order where the West dominates.

At the empirical level, researchers have utilized algorithmic audit methods to examine how text-to-image models represent Chinese contexts. Lan Xingyu et al. (2025) conducted an empirical study on six mainstream text-to-image models (including Midjourney) and identified three major issues when foundation models generate Chinese scenes: first, element errors, such as pseudo-Chinese characters, architectural structural errors, and spatio-temporal dislocation; second, cultural misinterpretations, such as folklore oversights and Westernized representation (element collage and style grafting); third, style contamination, such as exaggerated presentation (overly dilapidated or overly prosperous) and one-sided narratives. The study further revealed that Western models exhibit a significantly higher

frequency of Westernized representations and one-sided narratives than Chinese models, with Midjourney being particularly prominent in one-sided narratives. He Yuan et al. (2025) applied visual rhetoric theory to analyze images of China generated by four major text-to-image models, finding that real scenes accounted for a low proportion (only 19%), fictional content reached 63%, and modern China had a weak presence, leaving China largely depicted as an ancient state or traditional agricultural society. Dang Minghui et al. (2025) examined AI-generated war reporting images and found that AI systems harbor algorithmic biases that reinforce Western discursive authority in covert forms.

At the theoretical level, scholars primarily approach the topic from the perspectives of visual grammar and intelligent pseudo-environments. Yu Guoming et al. (2026) proposed the concept of an "intelligent pseudo-environment," arguing that generative AI is driving pseudo-environments to transition from symbolic representations to dynamic human-machine-environment cognitive couplings. In multimodal discourse analysis, the multimodal content analysis method proposed by Wang Yilei and Feng Dezheng (2026) provides a feasible path for systematic coding and quantitative analysis of large-scale multimodal corpora.

Looking across existing research, several gaps remain: first, a lack of systematic analysis treating "Chinoiserie" as a complete visual symbolic system rather than isolated elements; second, criticisms of Western models' cultural representations often remain at the level of phenomenological description without systematically exposing their representational mechanisms via visual grammar (color, composition, symbol selection); third, a lack of specialized and systematic analysis targeting Midjourney as a representative Western model. Given that Midjourney currently possesses the largest user base and most active algorithmic iterations among global text-to-image models, its visual reconstruction logic holds significant industry benchmark value and audit importance. Therefore, taking Midjourney as a case study, this research applies multimodal discourse analysis theories and methods to systematically examine the visual representational characteristics of "Chinoiserie" in Western AI image models, aiming to provide empirical evidence for AI governance in cross-cultural communication contexts.

Based on this context, this study focuses on three core research questions:

1. What characteristics do Midjourney-generated "Chinoiserie" images display across the three dimensions of visual grammar: representational, interactive, and compositional meaning ?
2. How do these visual characteristics construct the image of China ? Do systematic cultural and ideological biases exist, and how are they manifested ?
3. What data logics and power mechanisms underlie the symbolic representation of "Chinoiserie" by Western AI foundation models, and how can they be mitigated ?

2. Research Design and Methodology

2.1. Experimental Objective and Overall Logic

This study aims to explore the differential performance of the Midjourney generative AI model in reconstructing "Chinoiserie" visual discourse under different generative instructions. Using a comparative design, the experiment simulates two human-computer interaction scenarios: "vague instructions (no intervention)" and "precise instructions (professional constraints)". It constructs an image corpus covering three core domains: architectural space, costumed portraiture, and landscape atmosphere. The core logic is to control variables to reveal the algorithm's "cultural defaults" in its baseline state and its "translation efficiency" under professional knowledge intervention

2.2. Theoretical Framework: Visual Grammar Analysis

This study relies on the visual grammar framework proposed by Kress & Van Leeuwen (2006). This theory posits that images, as social semiotics, possess metafunctions similar to language: constructing representational meaning of the objective world, reflecting interactive meaning of social relations, and integrating compositional meaning of visual elements. Visual grammar provides a standardized framework to deconstruct AIGC images, translating complex cultural landscapes into quantifiable, auditable academic indicators

2.3. Prompt Design and Variable Control

To systematically analyze the biases and limitations generated by the algorithm, this study establishes two experimental variables: a baseline group and an experimental group. The baseline group uses macro, broad cultural labels to trigger the algorithm's default probabilistic distributions via simple prompts, thereby observing default cultural biases. The experimental group introduces professional terms with specific historical periods, structural norms, and aesthetic terminology to test the algorithm's semantic restoration capabilities when faced with high-context, high-professionalism requirements, as well as the corrective impact of professional knowledge on algorithmic bias. The prompts used are detailed in Table 1.

Table 1. Prompt Design Comparison Table for Sample Generation

Theme	Group ID	Prompt Type	English Prompt
Architectural Space	A	Baseline Group	A traditional Chinese palace building, ancient architecture style, highly detailed. 8k --v 6.1 --ar 3:2
Architectural Space	B	Experimental Group	Tang Dynasty palace architecture, massive Dougong brackets, hip roof (Fudian ding), red pillars, white walls, stone foundation, authentic Chinese timber structure, cinematic lighting --v 6.1 --ar 3:2
Costumed Portraiture	A	Baseline Group	A beautiful woman wearing traditional Chinese dress, oriental style, portrait --v 6.1 --ar 3:2
Costumed Portraiture	B	Experimental Group	A woman wearing Ming Dynasty Hanfu, Ao Qun style, cross-collar top, silk Mamian skirt with golden embroidery, historical accurate accessories, eye-level shot, neutral expression --v 6.1 --ar 3:2
Landscape Atmosphere	A	Baseline Group	Chinese style landscape painting, ink and wash, Zen atmosphere --v 6.1 --ar 3:2

Landscape Atmosphere	B	Experimental Group	Song Dynasty landscape painting style, Ma-Xia school composition, void negative space (Liu Bai), sparse ink brushstrokes, misty mountains, ink on silk texture --v 6.1 --ar 3:2
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2.4. Corpus Construction and Sample Selection

A total of 240 sample images were collected using a dual-gradient sampling method. For the three sub-themes (architecture, portraiture, landscape), each prompt set independently generated 40 valid samples. This sample size adheres to basic statistical significance requirements in content analysis, ruling out random variations in individual outputs to ensure empirical validity in extracting visual grammar features.

2.5. Quantitative Indicators of Visual Grammar

To convert qualitative analysis into quantitative statistics, this study adapted Kress & Van Leeuwen's visual grammar framework into a quantitative coding scheme tailored to AIGC images. Less relevant indicators (such as horizontal angle) were excluded, focusing research on six secondary indicators that best reflect cultural power dynamics and symbolic authenticity (Table 2). This selection prioritizes validity to deeply analyze algorithmic discourse hegemony and aesthetic homogenization in cultural representation.

Table 2. Quantitative Visual Grammar Coding Scheme for "Chinoiserie" AI Images

Dimension	Secondary Variable	Definition and Coding Criteria	Value Assignment
Representational Meaning	Conceptual Representation: Classificational Process	Performance of essential attributes of cultural symbols: whether accurate.	0 = Attribute Error
			1 = Attribute Ambiguity
			2 = Attribute Accuracy
Representational Meaning	Conceptual Representation: Analytical Process	Examination of the relationship between "part" and "whole".	0 = Structural Dislocation
			1 = Basically Reasonable Structure
Interactive Meaning	Contact	Eye contact between image participants and observers: direct gaze is "Demand", non-direct is "Offer".	1 = Demand
			2 = Offer
Interactive Meaning	Attitude	Perspective: Vertical angle (high/eye/low) represents power; horizontal angle (front/side) represents engagement.	1 = Low-angle (Power)
			2 = Eye-level (Equality)
			3 = High-angle (Scrutiny)
Compositional Meaning	Salience	Examines whether the most eye-catching elements are "authentic details" or "stereotypical cultural symbols".	1 = Stereotypical Symbols
			2 = Non-stereotypical / Authentic Details
Compositional Meaning	Framing	Connection or separation of visual elements; examines the proportion of non-entity space (Liu Bai).	0 = Low Negative Space (Liu Bai)
			1 = High Negative Space (Liu Bai)

3. Empirical Results and Analysis

3.1. Results and Analysis of Representational Meaning

Representational meaning examines how images construct reality through participants, processes, and circumstances (Kress & Van Leeuwen, 2006). In AIGC-generated Chinoiserie images, this dimension reflects the algorithm's accuracy and logical understanding when reconstructing traditional Chinese cultural codes. Quantitative statistics across the sub-indicators for the 240 samples are presented in Table 3.

Table 3. Percentage Distribution of Sub-indicators under "Representational Meaning"

Sub-indicator	Score Level	Arch A	Arch B	Costume A	Costume B	Landscape A	Landscape B
Classificational Process	2 Points: Accurate	22.50%	17.50%	0.00%	0.00%	100.00%	52.50%
Classificational Process	1 Point: Ambiguous	72.50%	82.50%	100.00%	75.00%	0.00%	47.50%
Classificational Process	0 Points: Error	5.00%	0.00%	0.00%	25.00%	0.00%	0.00%
Analytical Process	1 Point: Reasonable Structure	92.50%	87.50%	100.00%	87.50%	100.00%	100.00%
Analytical Process	0 Points: Structural Dislocation	7.50%	12.50%	0.00%	12.50%	0.00%	0.00%

1) Attribute Ambiguity and Semantic Vacuity of Cultural Subjects

Data indicates that Midjourney displays a distinct characteristic of "superficial resemblance lacking structural accuracy" when reproducing Chinese culture. This phenomenon is particularly prominent in concrete architectural and clothing themes.

In architecture, "generic ancient style" and element mixing are common. In Architecture Group A, images with attribute ambiguity reached 72.50%. Although images displayed contours of Chinese palaces, details exhibited a generic ancient style lacking specific dynasty specifications. Typical issues included plaque text resembling Chinese characters without actual meaning, roof styles switching randomly across Tang, Song, Ming, and Qing dynasties, and frequent contamination with Japanese Karafufu or Karesansui (dry landscape) elements. In Group B with professional terms, red pillars and corridors increased, but accuracy dropped slightly to 17.50% because the algorithm failed to grasp core codes like Dougong proportions and ritual hierarchy, showing superficial semantic processing.

In costume, structural deconstruction and symbol stacking occurred. The proportion of images scoring 2 points for accuracy in both costume groups was 0.00%. Baseline Group A masked tailoring inaccuracies by overusing Western stereotypical symbols of Oriental women, such as oil-paper umbrellas and golden hairpins. In experimental Group B, despite specifying "Ming Dynasty Mamian skirt," the

algorithm still mixed Qing Dynasty standing collars and oblique plackets with Ming Dynasty wide sleeves, with 25.00% of images containing outright attribute errors. This indicates the algorithm treats clothing as decorative textures rather than historically rigorous cultural artifacts.

2) Visual Stability vs. Semantic Rupture in Analytical Processes

The analytical process examines part-to-whole relationships. High scores in structural reasonableness across all groups reveal a core contradiction: AI masters physical logic to ensure visual plausibility and aesthetic appeal, but contains flaws in cultural logic. AI constructs a digital landscape that is visually coherent but culturally fragmented and arbitrary.

3) Style Adaptability Advantage in Landscapes

Compared to concrete subjects, the landscape group achieved higher accuracy (100.00% in Group A; 52.50% in Group B). This demonstrates that Midjourney's ability to capture abstract styles far exceeds its recognition of specific symbols. In Group B, accuracy fell because the algorithm could not precisely differentiate micro-level differences between the Southern Song Ma-Xia school and later Yuan/Ming/Qing brushwork, resulting in a generalized, blended Pan-Chinese aesthetic.

3.2. Results and Analysis of Interactive Meaning

Interactive meaning addresses social relationships established between image participants (people/objects) and observers (Kress & Van Leeuwen, 2006). This study analyzes Contact (Demand vs. Offer) and Attitude (Perspective) to examine power dynamics. Results show Midjourney exhibits marked "spectacularization" and "Othering" tendencies when generating Chinese elements (Table 4).

Table 4. Percentage Distribution of Sub-indicators under "Interactive Meaning"

Sub-indicator	Value Meaning	Arch A	Arch B	Costume A	Costume B	Landscape A	Landscape B
Contact	1: Demand	0.00%	0.00%	62.50%	70.00%	0.00%	0.00%
Contact	2: Offer	100.00%	100.00%	37.50%	30.00%	100.00%	100.00%
Attitude	1: Low-angle (Power)	42.50%	12.50%	0.00%	25.00%	25.00%	2.50%
Attitude	2: Eye-level (Equality)	57.50%	87.50%	100.00%	75.00%	75.00%	97.50%
Attitude	3: High-angle (Scrutiny)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

1) Contact Analysis

In the contact indicator, non-portrait and portrait groups showed contrasting interaction logics. Material landscapes were objectified, with architecture and landscape groups showing 100.00% Offer relationships, serving as static symbols for viewer inspection. Conversely, costume portrait groups showed high Demand gaze proportions (62.50% and 70.00%). AI tends to generate characters looking directly into the camera to build virtual engagement. Combined with costume inaccuracy, this direct gaze does not convey female agency but uses homogenized aesthetic figures to attract viewer attention.

2) Attitude Analysis

Vertical perspective reveals power balance between observer and subject (Kress & Van Leeuwen, 2006). In Architecture Group A, low-angle shots accounted for 42.50%. This low angle confers a surreal grandiosity and mystery upon ancient Chinese buildings, fitting Western stereotypes of Eastern civilization as "grand and mysterious" while creating visual spectacle. Introducing professional terms in Group B dropped the low-angle ratio to 12.50% and raised eye-level views to 87.50%, indicating professional vocabulary shifts the model from a cinematic spectacle mode to a documentary or survey-like presentation.

Costume Group B showed 25.00% low-angle perspectives after advanced clothing terms were added. The algorithm uses low angles to construct solemnity or splendor, which increases distance between observers and traditional culture, intensifying spectacularization.

3.3. Results and Analysis of Compositional Meaning

Compositional meaning focuses on spatial organization (Kress & Van Leeuwen, 2006). This study uses Saliency (stereotypical symbols) and Framing (Liu Bai / negative space proportion) to examine AI's grasp of Chinese spatial aesthetics (Table 5).

Table 5. Percentage Distribution of Sub-indicators under "Compositional Meaning"

Sub-indicator	Value Meaning	Arch A	Arch B	Costume A	Costume B	Landscape A	Landscape B
Saliency	1: Stereotypical Symbols	80.00%	100.00%	100.00%	95.00%	52.50%	40.00%
Saliency	2: Non-stereotypical / Authentic Details	20.00%	0.00%	0.00%	5.00%	47.50%	60.00%
Framing	1: High Negative Space (Liu Bai)	67.50%	25.00%	0.00%	0.00%	95.00%	100.00%
Framing	0: Low Negative Space (Liu Bai)	32.50%	75.00%	100.00%	100.00%	5.00%	0.00%

1) Saliency Analysis

Saliency measures focal elements. When professional prompts were introduced in Architecture Group B, stereotypical symbols as visual focal points rose from 80.00% to 100.00%. When responding to specific requests like "Dougong," the algorithm stacked high-frequency Oriental elements—such as red tones, dragon patterns, and lanterns—to fill the frame rather than using realistic structural logic. Costume groups maintained high stereotypical saliency across both rounds, solidifying traditional dress into visual tropes of bright red, embroidery, and gold accessories, while hiding structural craftsmanship.

2) Framing Analysis

Framing measured negative space (Liu Bai) to assess spatial distortion. Both costume groups scored 0.00% for negative space, relying on full-frame compositions that maximize visual saturation while stripping away Chinese aesthetics of void and balance. Architecture Group B experienced a sharp drop in negative space compared to Group A (from 67.50% down to 25.00%). The algorithm misinterprets high detail

density as professional quality, contradicting traditional architectural concepts of borrowed scenery and void spaces. The landscape group maintained high negative space (95.00% and 100.00%), proving AI applies negative space rules only when imitating Chinese ink painting styles, but reverts to Western painting paradigms emphasizing lighting saturation and detail density during 3D entity modeling.

3.4. Summary Findings

Across representational, interactive, and compositional dimensions, Midjourney-generated Chinoiserie images are digital simulacra reconstructed from globalized training data rather than authentic reflections of real culture.

1) Cultural Deconstruction and "Technical Distortion"

AI captures abstract stylistic traits well but suffers semantic ruptures with specific cultural symbols. As visual grammar posits, classification processes determine cognitive accuracy. Structural errors in rendering Mamian skirts and Dougong brackets demonstrate that algorithms without high-quality domain training produce technical bias, reducing Chinese culture in digital spaces to de-historicized visual templates.

2) "Othered" Power Imbalances

High frequencies of low-angle shots and demand-gaze interactions construct Orientalist narratives (Said, 1978), turning Chinese elements into exotic spectacles for Western gaze. This aligns with Lev Manovich's concept of "software aesthetics," where algorithms prioritize high visual impact over cultural agency.

3) Dissolution of Liu Bai via Aesthetic Homogenization

Maximizing visual salience leads to symbol stacking, erasing Liu Bai (negative space) under algorithmic demands for visual saturation. This homogenization highlights risks of generative AI executing digital cultural imperialism over non-Western civilizations through computational dominance.

4. Recommendations and Strategies

1) Incorporate High-Quality Domain Datasets for Training: Algorithmic bias stems from imbalanced, low-quality training data. Beyond generic web scraping, developer teams must construct specialized cultural datasets (e.g., historical costume databases, architectural survey records) and apply Reinforcement Learning from Human Feedback (RLHF) with cultural experts to calibrate algorithmic weightings.

2) Enhance Multi-Dimensional "Cultural Constraint" Prompt Algorithms: Because professional prompts can fail across certain dimensions, technical paths should explore knowledge-graph-assisted generation. When a user inputs "Ming Dynasty," the system should query verified cultural knowledge bases alongside pixel probability predictions.

3) Establish Non-Eurocentric Cultural Inclusivity Benchmarks: Breaking Western technical monopolies requires establishing multimodal evaluation standards for

cultural authenticity and inclusivity in generative AI. Metrics should combine symbolic recognizability, historical accuracy, and spatial aesthetic fidelity, compelling models like Midjourney and Stable Diffusion to respect cultural diversity in core algorithms and commercial iterations.

5. Conclusion

Although Midjourney can mimic specific styles, its reconstruction of Chinoiserie visual discourse shows superficial resemblance without structural accuracy, stripping symbols of historical depth. Symbolic collage and the loss of negative space reflect how Eurocentric training data marginalizes the cultural agency of non-core civilizations. Equal dialogue between algorithms and traditional cultural context must be restored through knowledge graphs and authenticity evaluation mechanisms.

This study has limitations. Although analyzing 240 samples, it focuses solely on Midjourney. Future research should compare cross-model performances involving Stable Diffusion, DALL-E 3, and Chinese models such as Wenxin Yige to evaluate generative AI's broader cultural communication characteristics.

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