Cross-Cultural Visual Traps of Generative AI: A Multimodal Discourse Analysis Based on Comparative Prompt Design

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Abstract. Generative AI is playing an increasingly prominent role in the advertising market. While it boosts production efficiency, it also triggers a series of cultural and ethical risks—the data-driven visual generation mechanism is systematically reproducing cultural stereotypes in cross-cultural advertising. This study takes Midjourney, a text-to-image artificial intelligence model, as the research tool and selects the American, Indian and Chinese markets as research objects. Two groups of prompts, stereotyped and de-stereotyped, are designed to generate 72 advertising samples, revealing the visual production logic of AI from the three dimensions of symbols, styles and narratives. The study finds that AI places non-Western modernity in a marked and interpreted other position: at the symbolic level, it presents a "festivalized representation", with the coverage rate of Chinese Spring Festival symbols reaching 75% and Indian ritual symbols being fully covered and stubbornly remaining even under intervention; at the stylistic level, it forms a "strong stylistic binding", with the intervention success rate in India being only 33.3%, far lower than 83.3% in the United States; at the narrative level, it replicates the "hegemonic narrative template", with 17% of Chinese individual images being endowed with additional emotional burdens. The conclusions of this study provide a critical perspective for understanding the cultural politics in the AI era.

Keywords: Generative AI, Cross-cultural Advertising, Stereotype, Visual Grammar, Multimodal Discourse Analysis, Cultural Bias.

1. The Origin of the Research Question: Why It Is Imperative to Examine the Cross-Cultural Visual Traps of AI

Generative AI is profoundly reshaping the production logic of the advertising industry in the form of an "efficiency revolution". Visual generation models represented by Midjourney and DALL·E, by virtue of their remarkable content generation capabilities, have made large-scale and personalized cross-cultural advertising production more convenient than ever before. However, behind this technology-driven efficiency upsurge, a sharp paradox has become increasingly prominent: when a technology that learns from existing data to match patterns is applied to cross-cultural communication which highly relies on cultural sensitivity, is its efficient output promoting equal dialogue between different cultures, or unconsciously and on a large scale automating inherent cultural biases?

Current debates mostly focus on the macro opportunities and risks of AI, or warn of its ethical issues at the theoretical level. In the specific field of cross-cultural communication, risks take the form of more hidden visual traps. According to the theory of "isomorphism of culture and communication", communication is by no means a transparent channel, and the process itself contains biases, which are intertwined and mutually reinforced with cultural biases. As a symbol production system based on massive existing data and pattern learning through complex algorithms, the technical core of generative AI determines that it is inevitably an imitation and reconstruction of existing cultural representations. Social semiotics points out that any visual text is a meaning system constructed by multimodal semiotic resources, and these symbols are deeply rooted in specific social and cultural practices. Therefore, when AI learns to generate an advertising image for a specific cultural group, it is not creating new meanings, but calling up and reorganizing the already existing, often unbalanced and stereotype-laden symbolic patterns in its training data.

This study thus raises a more specific question: through what specific visual mechanisms and production paths does generative AI solidify potential cultural biases into visible visual traps in cross-

cultural advertising production? To this end, this study takes images generated by Midjourney as the core analysis object, generates first-hand samples by designing cross-cultural advertising prompts, and combines multimodal visual discourse analysis to systematically deconstruct the reproduction logic of stereotypes from the three dimensions of symbols, styles and narratives.

2. Literature Review

With the popularization of generative artificial intelligence technology and the deepening of global economic integration, cross-cultural advertising production is experiencing a paradigm shift from human-dominated to human-machine collaboration. In this process, whether and how AI visual generation reproduces or reinforces cross-cultural stereotypes has become an important issue with both theoretical urgency and practical risks. Existing research mainly unfolds around the following three dimensions.

First, from the perspective of research on symbols and values in cross-cultural advertising, the core of cross-cultural advertising is to realize meaning transformation and cultural adaptation through symbolic systems, and the key to its success lies in the accurate conversion of cultural symbols and the adaptation of values. Most existing studies are carried out under classic frameworks such as Roland Barthes' semiotic theory and Geert Hofstede's cultural dimension theory, exploring how advertising achieves cultural adaptation through symbolic systems. Du Shihua further points out that cultural values directly regulate the symbolic forms and expression strategies of advertising. Such research provides theoretical tools for the symbolic dimension analysis of this paper—based on the semiotic tradition, we can ask: which cultural symbols does AI call up? How are these symbols combined? What logic underlies the selection of symbols?

However, most existing studies focus on the analysis of traditional advertising finished products, lacking investigation into the production process, especially the symbol generation mechanism under technical intervention. When generative AI intervenes as a "new actor" following data logic, the risks of symbolic distortion and value mistranslation it may trigger have become a new topic that urgently needs to be examined. Precisely because existing studies neglect the "black box" of the production process, this paper needs to shift the analysis anchor from finished products to the links of prompt design and human-machine interaction.

Second, from the perspective of research on the application and risks of generative AI in advertising production, generative AI is reconstructing the advertising production process as a "new actor", showing significant potential in improving creative efficiency and optimizing communication effects. Most existing studies from the perspective of technical efficiency and consumer response confirm that it can improve communication efficiency, perform better in rational appeal advertising, and AI models with high realism can also reduce consumers' sense of weirdness and improve purchase intention. Paths such as the human-machine collaboration metaphor model are committed to enhancing the anthropomorphism and creative quality of AI creation. Notably, some studies have also begun to explore the instrumental application of AI in assisting the identification and analysis of cross-cultural communication barriers. However, such studies mostly regard generative AI as a neutral efficiency tool, and the discussion of its risks generally focuses on universal dilemmas such as "content disconnection", "lack of humanistic values" or "effects being regulated by situational factors such as brands".

Most existing AI advertising studies focus on effects while neglecting texts, and multimodal discourse analysis studies mostly focus on human-created images without exploring how AI intervenes in the generation of visual meaning. When AI automatically matches visual styles according to the "co-occurrence frequency" in training data, colors and light and shadow that originally required human selection become statistical outputs of algorithms. This shift from intentional selection to pattern reproduction indicates that AI may not only call up wrong symbols, but also solidify a certain visual style as a default value, thus systematically reproducing cultural biases at the level of visual expression.

Third, from the perspective of interdisciplinary research on AI visual generation and cultural representation, existing research has revealed the systematic risk of generative AI solidifying biases in cross-cultural applications. Studies show that there are significant cultural differences in users' perception and use of AI tools—users from different cultural backgrounds form differentiated AI use motivations and experiences based on technological affordances, which challenges the assumption of its "cultural neutrality". At the same time, truly effective cross-cultural symbolic operation needs to rely on in-depth "ultra-localization" strategies, which is contrary to the AI's generation logic based on pattern matching. Experiments further confirm that even with the guidance of Hofstede's cultural dimensions, cultural roles generated by AI are still difficult to break away from stereotyped representations, exposing the structural limitations of its technical core. However, such discussions mostly regard AI as a neutral efficiency tool, failing to deeply reveal how its narrative generation mechanism interacts with the existing cultural power structure. Has AI created new narrative possibilities, or is it automatically replicating the hegemonic story templates accumulated by Western advertising for a century? This question is one of the core questions that this paper attempts to answer.

Although existing research has been carried out from the perspectives of cross-cultural symbolic adaptation and AI advertising application risks respectively, research that systematically and multi-dimensionally links the technical characteristics of generative AI with the generation mechanism of cross-cultural stereotypes is still insufficient. In view of this, this study intends to combine visual discourse analysis to reveal how generative AI systematically reproduces stereotypes in cross-cultural advertising production from the three dimensions of symbols, styles and narratives, so as to provide theoretical reference and practical enlightenment for responsible culture-adaptive advertising production.

3. Research Design

3.1. Research Object and Samples

This study selects Midjourney as the image generation tool, which is one of the most widely used text-to-image models in the field of advertising creativity, and its output results have typical reference value for examining the cultural representation logic of generative AI. To control irrelevant variables, the study introduces Coca-Cola as the analysis brand throughout the paper. As one of the most globalized consumer brands, Coca-Cola's advertising practice has always been in the dual tension of maintaining consistent global brand tone and adapting to local cultural symbols, making it an ideal carrier for observing how AI handles the relationship between cultural standardization and localization. According to the representative dimensions of cross-cultural research, three target markets are selected: the United States for observing the default representation mode of the model; India for observing AI's other-representation logic; China for testing whether AI has the ability to recognize non-Western modernity.

Different from most existing studies that focus on the content analysis of finished images, this study aims to explore how stereotypes are systematically produced rather than whether they are presented. Therefore, the comparative prompt experiment method is adopted. By actively designing and inputting text instructions with cultural directionality, the active detection of AI's visual production logic is realized under the premise of controlling core variables, and the research anchor is shifted from finished products to the production process. For each market, two groups of comparative prompts are designed (see Table 1): Group A (stereotyped group) invokes common cultural labels in mass media; Group B (de-stereotyped group) guides AI to generate images towards modern, daily and other directions with modified instructions. 12 images are generated for each group, and a total of 72 valid samples are obtained after screening.

Table 1. Design of Comparative Prompt Experiment

Market	Stereotyped Group (Group A)	De-stereotyped Group (Group B)
USA	White suburban family, backyard barbecue, flag, golden retriever, cola in ice bucket, warm summer, idealized	Multi-ethnic construction workers, high-altitude construction site in Chicago, cloudy day, tired but relaxed, documentary style, natural light
India	Traditional Indian family, Diwali ritual, sari, oil lamp, rangoli, gold ornaments, cola in copper plate, sacred warm light	Urban young women, Mumbai waterfront, jeans and T-shirt, mobile phone, modern high-rise apartment, daily evening, natural light
China	Multi-generational family, Spring Festival family reunion dinner, traditional courtyard, red lanterns, paper-cuts, dumplings and hot pot, red envelopes, pouring cola, red and gold warm tone	Young delivery riders, late-night alleys in Shanghai, electric scooter, delivery box, wet road after rain, neon light and shadow, tired but calm

3.2. Operational Path

This study formulates a multimodal coding table based on visual grammar and research question orientation (see Table 2). The coding covers three major dimensions of symbols, styles and narratives, with specific indicators such as character representation, scene symbols, color system, light and shadow processing, character relationship and emotional tone. Two coders independently completed the annotation of all 72 sample images. After reliability test, the coding consistency coefficient reached 0.89, which meets the acceptable standard. The coding results are derived in the form of frequency statistics and cross analysis, providing data support for subsequent discourse interpretation.

Table 2. Design of Multimodal Coding Table

Analysis Dimension	Coding Category	Coding Indicator	Operational Definition
Symbolic Dimension	Character Representation	Skin color/Clothing/Age/Gender/Occupation	Racial characteristics, dressing style, age group, gender composition and occupational identity implication of characters
	Scene Symbols	Indoor/Outdoor/Urban/Natural/Traditional architecture/Modern architecture	Spatial type and its cultural attributes where the picture takes place
	Props and Utensils	Traditional utensils/Technological products/Religious symbols/None	Items with cultural identification significance in the picture
Stylistic Dimension	Color System	Main hue/Saturation/Contrast/Cold-warm tendency	Overall color tendency and visual tone of the picture
	Light and Shadow Processing	Natural light/Dramatic light/High contrast/Soft transition	Light source and texture characteristics of the picture
	Composition Paradigm	Central composition/Golden section/Symmetry/Pitch angle	Visual organization mode and shooting angle of the picture
Narrative Dimension	Character Relationship	Family/Workplace/Individual/Community/No clear relationship	Interaction and social connection between characters
	Emotional Tone	Warm/Conflict/Tranquil/Carnival/Mysterious/None	Overall emotional connotation conveyed by the picture
	Timeliness	Traditional/Modern/Future/Nostalgic/Ambiguous	Historical period or temporal texture implied by the picture

4. Research Findings: Three Visual Mechanisms of Generative AI in Reproducing Cross-Cultural Stereotypes

Through multimodal coding and discourse analysis of 72 generated samples, the study finds that generative AI systematically reproduces stereotypes in cross-cultural advertising production. Its mechanism is not scattered symbol misuse, but locking non-Western cultures in a specific visual framework through three interlocking dimensions: narrow invocation of symbols, strong binding of styles and template replication of narratives.

These three dimensions are progressive and mutually reinforcing, together forming a complete visual grammar system. The symbolic dimension is the basic component of cultural representation, determining which symbols are used to identify cultural identity in the picture; the stylistic dimension is the organizational strategy and emotional shaping of symbols, stipulating how symbols are viewed and encoding the power distance of viewing; the narrative dimension integrates symbols and styles into an understandable story template, revealing who is doing what. Symbols provide visual vocabulary, styles stipulate grammatical rules, and narratives weave vocabulary and rules into stories. The three mechanisms interact with each other, turning stereotypes from occasional symbolic deviations into a visual production device that can be mass-produced and infinitely replicated.

4.1. Symbolic Dimension: Festivalized Narrowing and Keyword Overweight of Cultural Symbols

Symbols are the visual carriers of cultural meaning. Character costumes, scene spaces and props together weave the identity imagination of a specific culture. However, when generative AI becomes the producer of these symbols, its selection and combination of symbols present a highly patterned narrowing logic: AI tends to lock the visual presentation of a certain culture in a few festival scenes that can be mass-produced, making festival symbols the default visual equivalent of the culture.



Figure 1. Sample Examples Generated by Comparative Prompt Experiment (China)

This mechanism is particularly classic in the samples of the Chinese market. As shown in Table 3, in the Chinese Group A samples, the occurrence frequency of Spring Festival-related symbols such as red lanterns and paper-cuts accounts for 75% of all cultural symbols in this group. This means that in AI's visual database, a nearly equivalent mapping relationship is established between "Chinese culture" and "Spring Festival culture". AI's this festivalized representation strategy narrows the visual presentation of a certain culture to a few festival scenes, making festival symbols the default visual equivalent of the culture, while the diversity of daily life is systematically omitted. More illustrative is the data of Group B. Even when the instructions clearly require non-festival scenes such as "young delivery riders" and "late-night alleys in Shanghai", there is still an abnormal invasion of 25% Spring Festival symbols such as red lanterns and red light signs. This means that specific cultural symbols overflow from the original festival context and become cultural keywords that AI will call up by

default when representing the culture regardless of the context adaptation. Certain words deeply bound to specific cultures have an abnormal weight in the model's semantic-visual mapping space. Even if negative or modified instructions such as "modern" and "daily" are input, it is difficult to effectively offset the model's inertia of calling stereotyped symbols.

Table 3. Statistics of Spring Festival Symbols in the Chinese Market

Market	Analysis Dimension	Coding Indicator	Number of Occurrences (times)	Total Number of Symbols (pieces)	Proportion of Occurrences (%)
Chinese Market	Symbolic Dimension	Spring Festival symbols in Group A	216	288	75%
		Spring Festival symbols in Group B	48	192	25%

Indian samples present a more stubborn symbol monopoly. In the Indian Group A samples, the occurrence rate of traditional ritual symbols is as high as 100%—all pictures are locked in highly ritualized scenes such as Diwali and weddings. Although the Group B samples successfully remove explicit traditional elements such as palaces and idols under instruction intervention, golden tones, complicated patterns and decorative details still remain highly. These symbols are not required by the instructions, but are cultural marks actively added by AI, as if the pictures are not enough to be identified as Indian without these decorations. In all 24 Group B samples of China and India, the number of neutral symbols representing contemporary urban daily life such as white-collar workers returning home from get off work is zero. The contemporary life of the two countries presents a fragmented picture in AI's visual grammar: either it is the festival finery (Group A), which can be appreciated; or it is the tired delivery riders at midnight and riders in alleys after rain (Group B), which can be narrated. The only thing missing is the daily state that does not need explanation or meaning assignment.



Figure 2. Sample Examples Generated by Comparative Prompt Experiment (India)

However, the narrowing of symbols is only the superficial part of the problem. When these narrowed symbols are presented with specific colors and light and shadow, the deeper cultural bias truly emerges.

4.2. Stylistic Dimension: Strong Binding of Visual Grammar and Hierarchization of Aesthetics

Style is the cultural coding at the level of visual grammar. Color, light and shadow, and composition together form the emotional tone and aesthetic orientation of an image. If the symbolic dimension answers what elements are used, the stylistic dimension asks how these elements are

presented. The study finds that AI not only allocates specific symbols to non-Western cultures, but also allocates an almost unchangeable visual style—this strong stylistic binding mechanism makes the aesthetic diversity within non-Western cultures systematically eliminated.

Indian samples are the most typical example. When the Group B prompts clearly require "daily evening" and "natural light", the images generated by AI still stubbornly retain a layer of warm golden filter: the sunset is rendered too strong, the characters' skin color is coated with a golden halo, and the overall saturation is significantly higher than that of the American samples under the same conditions. This visual grammar encodes Indian culture as an exotic style for Western consumption—strong, gorgeous and full of drama, but lacking the texture of daily life.

In contrast, for the American samples, the execution accuracy of the same instructions of "cloudy day" and "natural light" is as high as 83.3%. The cold tone of cloudy days is accurately presented: the light is soft and restrained, and the color restoration is realistic. This contrast exposes the power structure at the level of visual grammar: Western aesthetics is set as an unmarked default value by algorithms—it does not need to be named or explained, it is just "natural"; while non-Western aesthetics must be marked and shaped, becoming a style that needs special explanation. Data confirms this asymmetric power relationship: the style intervention success rate of Indian samples is only 33.3%, and most images retain the exotic mark of warm golden color regardless of the instructions (see Table 4).

Table 4. Statistics of Style Intervention Effects in the Indian and American Markets

Market	Analysis Dimension	Coding Indicator	Successful (pieces)	Total (pieces)	Success Rate (%)
Indian Market	Stylistic Dimension	Style intervention effect in Group B	4	12	33.30%
American Market		Style intervention effect in Group B	10	12	83.30%

This is exactly what Gunther Kress and Theo van Leeuwen have revealed—visual grammar is never a neutral form, but a carrier of ideology. When the West can present the fatigue of workers with cloudy days, the alienation of cities with cold tones, and the reality of life with natural light, while non-Western countries are always locked in the warm golden exotic style, the visual grammar itself becomes the bearer of hierarchical order. It permanently places the represented in the viewed other position, while the viewer hides behind the transparent visual conventions.

However, the solidification of style is only the superficial coding at the level of visual grammar. When these symbols beautified by the warm golden filter are woven into a specific story template, another deeper cultural discipline truly unfolds—narrative determines who is qualified to be the protagonist of the story and what stories they are allowed to tell.

4.3. Narrative Dimension: Automated Replication of Hegemonic Story Templates and Obscuration of Cultural Subjectivity

Symbols provide vocabulary, styles stipulate grammar, and narratives weave vocabulary and grammar into understandable stories. The study finds that without any relevant cultural instruction intervention, AI will automatically call up the stereotyped narrative templates accumulated by Western commercial advertising for a century, and migrate this set of templates to the representation of non-Western markets, resulting in narrative dislocation and obscuration of cultural subjectivity.

The default group of the United States repeatedly presents a classic narrative archetype of "suburban nuclear family sharing family happiness": parents and children are in a tidy living room, and products and emotions complete a ritualized connection. This set of narrative templates is completely migrated to the Indian Group A samples: although the characters change into traditional costumes and the background becomes palace buildings, the core of the story remains unchanged—it is still the nuclear family, the happy reunion, and the ritualized connection between products and

emotions. Coding data shows that the occurrence rate of nuclear family narrative in 12 Indian Group A samples reaches 100%.

The problem is not that AI executes the family instruction—we did input "traditional Indian family" in Group A. The real question worth asking is: when the family does not appear in the prompts, how does AI decide when to present the family and when to present the individual? Data reveals the narrative association logic of AI. In the Chinese and Indian Group B samples, due to the instructions shifting to modern, urban and daily, the characters in the pictures switch from family to individual—83% of the 12 Chinese Group B samples show individual solitude scenes, presenting images such as late-night delivery riders and riders in alleys after rain; 92% of the 12 Indian Group B samples show scenes of urban women in groups (see Table 5). On the surface, AI perfectly executes the instructions. But when this phenomenon is compared with the American default group, the deep-seated problem emerges: in the American context, modern daily life can include family living room TV time, but in the non-Western context, modernity must be stripped of family to prove its progressiveness. This template replication simplifies the complexity of non-Western cultures into a "mirror of the other" defined by the West, obscuring cultural subjectivity.

Table 5. Statistics of Character Presentation in Chinese and Indian Group B Samples

Market	Analysis Dimension	Coding Indicator	Successful (pieces)	Total (pieces)	Success Rate (%)
Indian Market	Narrative Dimension	Individual solitude in Group B	10	12	83
American Market		Urban women in groups in Group B	11	12	92

5. Conclusions and Discussion

The study finds that generative AI does not simply present stereotypes in cross-cultural advertising production, but systematically reproduces them through a complete visual grammar system. Based on the multimodal discourse analysis of 72 generated samples, the study reveals that the three interlocking mechanisms of festivalized narrowing at the symbolic level, strong binding of visual grammar at the stylistic level and replication of hegemonic templates at the narrative level lock non-Western cultures in a specific viewing framework, making outdated biases gain a new expression form with the appearance of technical neutrality.

These three mechanisms are not isolated from each other, but progressive and mutually reinforcing. The festivalized narrowing of symbols compresses non-Western cultures into a few festival symbols that can be mass-produced, making modern daily life systematically omitted; the strong stylistic binding equips these symbols with an almost indelible visual filter, with India locked in warm golden tones and the West occupying a transparent default position; the replication of narrative templates further integrates symbols and styles into consumable story templates, obscuring the complex historical paths and diverse possibilities in the process of global modernity in the binary binding of "traditional/family" and "modern/individual". The joint action of the three mechanisms makes AI not only replicate stereotyped symbols, but also replicate the viewing power structure behind the symbols.

The theoretical contributions of this study are mainly reflected in three dialogues with existing literature. First, the advancement of cross-cultural semiotic theory. Most existing studies focus on the symbolic analysis of advertising finished products, with the implicit premise that symbol selection is the result of human planning. The study finds that after the intervention of AI, symbol selection becomes a statistical output of the "co-occurrence frequency" in training data. Therefore, cross-cultural semiotic theory needs to introduce the dimension of "technical mediation" to re-examine the fundamental question of who is selecting symbols. Second, the supplement to visual grammar theory. Gunther Kress and Theo van Leeuwen's visual grammar theory reveals how color, light and shadow, and composition jointly construct meaning, but its analysis objects are always human-created images. The study finds that AI not only calls up symbols, but also calls up style templates, forming a

phenomenon of "strong stylistic binding". Third, the deepening of research on AI cultural bias. Most existing studies only stop at the phenomenon description of AI bias, and this study further reveals the specific mechanisms of bias generation—festivalized representation, strong stylistic binding and hegemonic narrative replication. These three mechanisms not only answer "what biases exist", but also answer "how biases are produced".

Of course, this study also has several limitations. This study only selects three markets: the United States, India and China. Although they have cross-cultural representativeness, they fail to cover more diverse cultural contexts (such as Africa, Latin America and Central and Eastern Europe). Future research can be extended to more cultural circles to test the universality of concepts such as "festivalized representation". Although the comparative prompt experiment can actively detect the generation logic of AI, it cannot fully simulate the human-machine collaboration process in real advertising production. Real advertising creativity often experiences multiple rounds of prompt debugging, manual screening and post-production modification. This study presents the results of a single generation and fails to capture the dynamic process of human-machine interaction.

In summary, the essence of the visual traps of generative AI in cross-cultural advertising production is not technical failure, but the natural extension of the global cultural power structure in the algorithm era. When Western modernity occupies the unmarked default position, and non-Western modernity always needs to be marked, explained and valued, what we see is not only the bias of AI, but also the digital remains of colonial gaze for hundreds of years. Exposing the operation logic of this set of visual grammar is the first step of criticism; and the real challenge lies in how to rebuild the equality and diversity of cultural representation in the algorithmic world.

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