Cross-Border Communication and Clothing Design Strategies for Fashion Brands in Film and Television Media

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ABSTRACT Cross-border fashion communication in film and television requires the consistent transmission of brand identity through dynamic visual environments, where the optical behavior of textile materials, semantic representation, and character attributes jointly influence audience perception. From the perspective of electromagnetic wave interaction in the visible spectrum, variations in fabric reflectance and imaging conditions further affect the stability of visual symbols across heterogeneous media platforms, highlighting the importance of integrated perception and feature fusion strategies. This study proposes a computational framework for cross-border clothing design that combines character analysis, brand-value mapping, parametric garment generation, and retrospective verification within a unified semantic workflow. An improved BERT model and convolutional neural network are employed to extract multimodal features, while textile optical properties, including ASTM-standardized reflectance spectra, drape characteristics, dynamic deformation, and color perception in the CIELAB space, are incorporated into material selection and structural optimization. Motion capture and visual-symbol encoding are further integrated to establish adaptive correspondence between garment configuration and narrative requirements, and multimodal verification is conducted using clothing symbol consistency and cross-platform brand stability metrics. Experimental results demonstrate that the proposed framework effectively improves the coherence of brand representation in dynamic media environments, achieving a cross-platform stability rate of 0.95 for silk materials and a clothing matching degree of 0.97 under high-drape conditions. The proposed methodology provides a quantitative design paradigm that integrates textile optics, multimodal perception, and semantic analysis, offering potential methodological reference for electromagnetic sensing, intelligent visual communication, and cross-media information propagation.

INDEX TERMS textile optics, multimodal perception, semantic mapping, cross-media communication, electromagnetic sensing

I. INTRODUCTION

COMBINING fashion with film and television is essential for brand communication because it utilizes narrative and visual impact to incorporate brand symbols into character clothing [1,2]. However, existing research generally focuses on the communication effects of film and television media and brand market feedback, lacking in-depth exploration of how clothing design can systematically support cross-border communication [3,4]. Methodological deficiencies exist in the visual performance of textile materials in film and television environments, as well as in the relationships between color symbols and psychological perception, the function of clothing modeling in narrative advancement, and the unity of craftsmanship details and brand identity [5,6]. Especially in film and television lighting environments, the optical reflectivity properties of different fiber types (natural, synthetic, or blended) vary significantly, resulting in noticeable color differences within the same brand color across lenses. There is a lack of systematic research on the impact of fabric structure (plain, twill, or satin) on light and shadow gradation [7,8]. Professional standards have not yet been established for the special requirements of film and television shooting regarding the dynamic performance of textile materials (such as the formation of wrinkles in motion). These technical challenges within the textile industry directly impact the accuracy and consistency of brand visual symbols in film and television communication [9,10]. The lack of design support means that fashion brands' presentations in film and television often remain superficially symbolic, failing to establish a stable communication path [11]. This impedes consistent cultural value expression through clothing, as core brand elements exhibit instability across media, failing to align precisely with character positioning [12].

Despite progress in media communication research, the lack of an integrated clothing design methodology hinders the transmission of deep brand value. Cheng B. [13]'s historical text analysis of "Two Stars in the Milky Way" (1932) revealed the cross-media cultural consciousness demonstrated by early filmmakers during the transition from silent to sound, through narrative structure and the exploration of national consciousness, providing a historical reference for brand communication. With the development of media technology, the form of advertising integration has shifted from static to dynamic interaction. Lin H. F. [14] et al. confirmed through experimental research that there are significant cultural differences in the effects of augmented reality advertising. American audiences have a deeper memory for placements inconsistent with the program, while Taiwanese audiences prefer dynamic title advertisements that are consistent with the program. Hatzithomas L. [15] et al.'s cognitive research in the digital environment further showed that the synchronization and fit of cross-media advertising regulate brand attitudes by affecting subjective understanding. Despite advances in communication effects and audience cognition, existing research remains focused on surface phenomena and lacks a systematic methodology for integrating clothing design into brand value transmission, which contributes to challenges in maintaining brand cultural value integrity during visual transformation.

Contemporary brand communication acknowledges clothing's value-carrying role, yet lacks a systematic framework linking design parameters to communication objectives. Jang S. Y. [16] et al., by analyzing online fabric retail platforms and interviewing 25 designers, revealed the limitations of visual and textual information in conveying the tactile properties of fabrics, and constructed a theoretical framework and practical guidelines for tactile communication of fabrics in a digital environment, providing a path for the precise expression of material properties. Castillo-Abdul B. [17] et al. studied 92 corporate social responsibility contents published by three luxury brands, including Gucci and Prada, on Instagram, Facebook, and TikTok. The study found that their communication focused on themes of sustainable materials and ecological protection, with the highest interaction in the form of videos and scrolls. Co-branded content significantly increased brand influence and indicated a strategic orientation toward deployment in the Asian market via TikTok, supported by localization projects for cross-cultural value transmission. Diaz-Bustamante-Ventisca M. [18] et al. conducted a survey on five fast fashion brands, confirming that consumers generally have a perception of greenwashing, and this perception is exacerbated when brands are disseminated through advertising, influencers, and official websites, and is positively correlated with sustainable consumption behavior. Existing research has advanced understanding of communication channels and audience response, yet a systematic mapping mechanism linking clothing design parameters to brand value remains absent. Core dimensions, including the optical performance of textile materials, color psychology, structural narrative, and craft identification, are not integrated into a unified methodological framework.

This paper aims to construct a clothing design strategy system for cross-border communication within film and television media. Centered on a tripartite semantic mapping framework of film and television characters – brand positioning – clothing design, this system forms a systematic methodological approach. Craft brand identification, color psychological effects, structural narrative function, and material expressiveness based on the optical properties of textile materials are the four elements of this approach. Through a closed-loop process consisting of character symbol analysis, semantic association construction, parametric design implementation, and retrospective verification, this approach ensures that brand cultural values are consistently expressed in visual communication. This paper presents a systematic approach that integrates character analysis, design execution, and verification to transform film and television clothing from a simple form into a medium that guarantees stable cultural value transmission and advances design methodology.

II. CONSTRUCTION OF FASHION BRAND CLOTHING DESIGN STRATEGY FOR CROSS-BORDER COMMUNICATION IN FILM AND TELEVISION

EXTRACTION OF VISUAL SYMBOLS FROM FILM AND TELEVISION CHARACTERS BASED ON NARRATIVE ANALYSIS

A three-part semantic mapping framework that connects character traits, brand value systems, and clothing design specifications forms the basis of the analysis. Multimodal feature fusion technology and organized data collection are the foundations for the extraction and data encoding of movie and television character symbols. Screenplay text, video, and character image description documents are the input sources. The data table structure of the character database, which uses a distributed storage architecture, comprises five fundamental fields: character number, scene context, dialogue content, behavior, and visual expression. Tokenization and named entity recognition are used in a specific module to process the script text [19,20]. An improved BERT architecture with a 12-layer encoder, 768-dimensional hidden states, and 12 attention heads is used to generate semantic features using a 30,000-token custom-trained vocabulary. For fine-tuning on domain-specific data, the model uses a learning rate of 2×10^{-5} and a maximum sequence length of 512 tokens. Text feature extraction uses a semantic weight calculation method:

$$W_{ij} = \frac{tf_{ij} \times \log\left(\frac{N}{df_i+1}\right) \times |\alpha_i|}{\sum_{k=1}^{M}\left(tf_{kj} \times \log\left(\frac{N}{df_k+1}\right) \times |\alpha_k|\right)} \tag{1}$$

where, W_{ij} represents the normalized weight of the i-th feature word in the j-th character description; tf_{ij} is the word frequency; N represents the total number of character descriptions within the dataset; df_i is the number of characters containing feature word i; α_i is the sentiment polarity coefficient of the feature word, which is obtained by linear transformation after the pre-trained BERT model predicts the sentiment tendency of the feature word, ranging from [-1, 1]; M is the total number of feature words.

Visual feature extraction is defined as follows:

$$F_v = \frac{1}{T}\sum_{t=1}^{T}\mathrm{CNN}(I_t) \tag{2}$$

where, F_v represents the visual feature vector of character v; T is the total number of frames in which character v appears in the film or television work; I_t is the image of frame t; $\mathrm{CNN}(\cdot)$ denotes a two-dimensional convolutional neural network, specifically ResNet-50 pre-trained on ImageNet, which processes each frame independently to extract spatial features without temporal weighting or motion-aware pooling mechanisms.

The manual annotation and automatic extraction results are integrated using a weighted fusion algorithm:

$$S_r = \beta' \cdot S_{\mathrm{manual}} + (1-\beta)\cdot S_{\mathrm{auto}} \tag{3}$$

To ensure that the final symbolic representation retains a statistically consistent distribution with the original data, this weighted fusion algorithm employs preset weight coefficients to balance the contributions of automatic extraction results and manual annotation. To reduce the variance of the fused representation, the weight coefficients are determined by analyzing the error distribution between the two data sources. where, S_r represents the final symbolic representation of character r; S_{manual} is the manual annotation score vector; S_{auto} is the automatically extracted feature vector; β' is the manual annotation weight coefficient, ranging from [0.4, 0.6].

Using the Five-Factor Model (FFM), which comprises five primary dimensions—extraversion, agreeableness, conscientiousness, emotional stability, and openness—character personality dimensions are organized. The construction of narrative function labels, which consist of 36 subcategory labels and 12 core narrative function categories, is based on Propp's narrative function theory.

Three levels of quality control are implemented during data encoding: Level 1 regulates the original data's integrity; Level 2 regulates the precision of feature extraction; and Level 3 regulates the consistency of the symbolic representation. Details are displayed in Table 1.

TABLE 1. Film and Television Character Data Structure

Field Name	Data Type	Value Range
Character Number	String	VARCHAR [12]
Extraversion		
Agreeableness		
Conscientiousness	Floating Point Numbers	[0.000, 1.000]
Emotional Stability		
Openness		
Main Categories of Narrative Functions		[1, 12]
Narrative Function Subcategory		[1, 36]
Age Range	Integer	[1, 5]
Gender Orientation		[1, 3]
Education		[1, 4]
Income Level		[1, 5]
Value Orientation		[1, 10]
Lifestyle Preferences		[1, 8]

Table 1 outlines the structural framework of character data encoding, which facilitates the quantitative analysis process of brand value mapping and design parameter generation, realizes the systematic conversion from raw descriptions to calculable parameters, and acts as the fundamental carrier for the quantitative representation of character features.

The logical relationship between data preprocessing, feature extraction, and symbolic representation is embodied in Figure 1, which shows the technical path from multi-source input to structured output for character symbols. This creates an intermediate conversion mechanism that links character features with parameters of clothing design.

SEMANTIC ASSOCIATION AND MATCHING MODEL BETWEEN CHARACTER SYMBOLS AND THE BRAND VALUE SYSTEM

By using a quantitative matching algorithm between the brand value vectors and the character trait vectors, this framework operationalizes the relationship. The three-dimensional spatial model that makes up the brand value system is composed of three vectors: market positioning, core values, and cultural elements. The market positioning vector includes target demographics, price range, and consumption scenarios; the cultural element vector includes historical heritage, artistic expression, and social responsibility; and the core value vector includes innovation, quality, and uniqueness.

A five-point Likert scale is used to standardize each dimension in Table 2 and create a computable brand value vector space, which facilitates quantitative analysis of the character-brand semantic association.

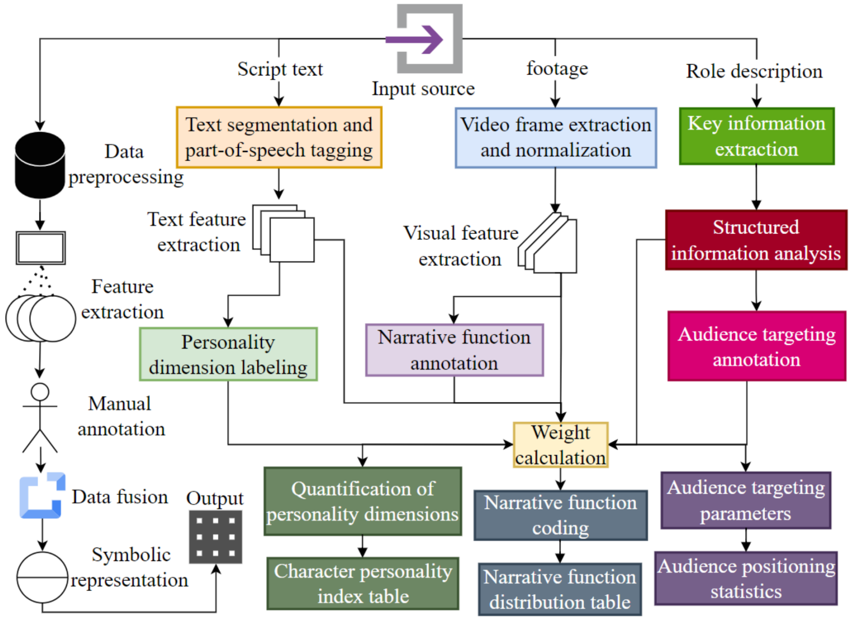

FIGURE 1. Film and Television Character Symbol Extraction and Encoding

TABLE 2. Brand Value System Data

Field Name	Data Type	Value Range
Brand Number	String	VARCHAR [10]
Cultural Elements Vector		
Core Value Vector	Floating-Point Array	[0.000, 1.000]
Market Positioning Vector		

Weighted cosine similarity is used to determine how similar the character trait vector and the brand value vector are to each other:

$$\begin{aligned} S(r,b) =&\alpha \cdot \frac{V_{\text{char}}(r)\cdot V_{\text{cult}}(b)}{\|V_{\text{char}}(r)\|\cdot\|V_{\text{cult}}(b)\|} \\ &+\beta\cdot\frac{V_{\text{narr}}(r)\cdot V_{\text{core}}(b)}{\|V_{\text{narr}}(r)\|\cdot\|V_{\text{core}}(b)\|} \\ &+\gamma\cdot\frac{V_{\text{aud}}(r)\cdot V_{\text{mark}}(b)}{\|V_{\text{aud}}(r)\|\cdot\|V_{\text{mark}}(b)\|} \end{aligned} \tag{4}$$

S(r,b) represents the similarity between role r and brand b; $V_{\text{char}}(r)$ represents the role personality trait vector; $V_{\text{narr}}(r)$ represents the role narrative function vector; $V_{\text{aud}}(r)$ represents the role audience positioning vector; $V_{\text{cult}}(b)$ represents the brand cultural element vector; $V_{\text{core}}(b)$ represents the brand core value vector; $V_{\text{mark}}(b)$ represents the brand market positioning vector; the character trait vector is generated by the narrative analysis module and includes three sub-vectors: personality, narrative function, and audience positioning. The brand value vector is constructed based on brand profile data and covers the three dimensions of cultural elements, core values, and market positioning. All vectors are standardized using a five-point Likert scale. α, β, and γ represent the dimension weight coefficients, satisfying $\alpha+\beta+\gamma=1$. The multi-dimensional matching calculation formula is:

$$M(r,b)=\sum_{i=1}^{3} w_i\cdot\cos(\theta_i) \tag{5}$$

where, M(r,b) represents the final matching degree; w_i represents the weight coefficient for the i-th dimension; θ_i represents the angle between the corresponding vectors.

The matching process between character and brand trait vectors in multidimensional space is depicted in Figure 2. Three vectors are identified for the character symbolic data: audience positioning, narrative function, and personality; similarly, three vectors are identified for the brand value system: market positioning, cultural components, and core values. By feeding the six-vector input into a weighted cosine similarity algorithm for calculating spatial distance, a character-brand matching matrix is produced, allowing symbolic features to be systematically converted into design parameters.

The matching values for every character and brand are stored in the character-brand matching matrix, where each matrix element represents the degree of matching between the character and brand. The basic input for creating clothing design parameters consists of matrix rows that correspond to character numbers and columns that correspond to brand numbers. The semantic mapping process implements a double-blind verification mechanism, with verifiers independently evaluating brand background and character information. Remapping is initiated when discrepancies exceed a threshold.

PARAMETRIC CLOTHING DESIGN STRATEGIES FOR CROSS-BORDER COMMUNICATION

The four-dimensional expansion of clothing design uses the matching parameters output by the character-brand mapping

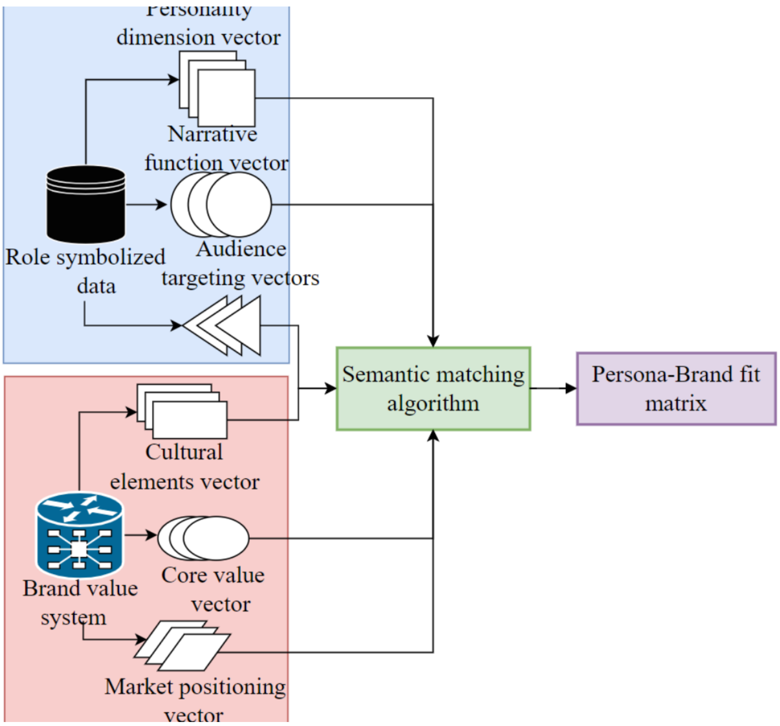

FIGURE 2. Semantic Mapping Mechanism

matrix to transform semantic associations into executable design instruction sets. The design process uses the matching degree between the brand value vector and the character feature vector as a constraint and conducts parametric design across four specialized dimensions: textile material expressiveness, color psychological effects, structural narrative function, and craftsmanship brand identity.

The material dimension establishes a mapping relationship between the optical properties of fabrics and the lighting conditions of film and television environments. A spectrophotometer (ASTM (American Society for Testing and Materials) E308-18 standard) is used to measure the reflectance curves of different textile materials under standard illuminants D65 (5,600 K) and A (3,200 K). This yields a set of material performance parameters $M = \{m_1, m_2, \ldots, m_n\}$, where m_i represents the reflectance value of the i-th material at wavelength λ, ranging from [0, 1]. The material selection algorithm is defined as follows:

$$S_m = \alpha_1 \cdot C(\lambda) + \beta_1 \cdot T + \gamma_1 \cdot D \tag{6}$$

where, S_m represents the material compatibility score; $C(\lambda)$ represents the color saturation at wavelength λ; T represents the structural complexity of the textile material; D represents the deformation stability of the material in dynamic shots; α_1, β_1, and γ_1 are weight coefficients that sum to one, derived from the normalized output of the character-brand matching matrix, ensuring alignment with the semantic association strength.

Notes: ASTM D1388 is used to test the drape coefficient, which measures a fabric's ability to hold its shape in static situations; ISO 105-B02 is used to test colorfastness; and the dynamic deformation index, which measures the normalized change in surface contour over time, is used to quantify the formation of wrinkles in fabrics under controlled cyclic motion. Lower values indicate greater resistance to dynamic distortion. A mapping relationship between material properties and character performance is established in Table 3, which also quantifies the important performance parameters of textile materials in film and television environments. In addition to addressing the lack of quantitative standards for material selection in film and television clothing design, the data provides empirical evidence for the weight coefficients in the material dimension algorithm by confirming that a material combination with a high drape coefficient (>0.70) and a low dynamic deformation index (<0.40) can simultaneously meet the requirements of character expression and camera dynamics.

TABLE 3. Key Performance Parameters of Textile Materials in Film and Television Environments

Material Type	Fiber Content	Fabric Structure	Warp and Weft Density (ends/picks per 10 cm)	Drape Coefficient	Color Fastness (Grade)	Dynamic Deformation Index	Applicable Role Types
Silk	100% Mulberry Silk	Satin	420 × 380	0.78	4.2	0.35	Elegant/Noble
Flax	100% Flax	Plain Weave	280 × 260	0.42	3.8	0.62	Natural/Literary
Cotton	100% Cotton	Twill	320 × 290	0.55	4.0	0.48	Friendly/Everyday
Polyester	100% Polyester	Tight Knitting	350 × 330	0.38	4.5	0.28	Modern/Workplace
Blended	65% Cotton + 35% Polyester	Plain Weave	300 × 280	0.52	4.3	0.42	Multifunctional
Jacquard Fabric	70% Silk + 30% Polyester	Jacquard	450 × 400	0.72	4.1	0.32	Luxury/Ceremony

Using the CIELAB color space for quantitative representation, the color dimension builds a database of color psychological effects. The following is the definition of the color emotion mapping function:

$$E(c) = \sum_{i=1}^{12} w_i \cdot p_i(c) \tag{7}$$

where, $E(c)$ is the emotional valence of color c; w_i is the weight coefficient of the i-th psychological dimension; $p_i(c)$ is the projection value of color c on the i-th psychological dimension. The psychological dimensions include warmth, vitality, and refinement. The weight coefficient w_i is determined by the degree of match between the brand's core value vector and the character's personality dimension.

The structural dimension generates clothing structural parameters based on character motion capture data, establishing a model for matching the clothing silhouette with the character's motion trajectory. The formula for calculating structural fit is:

$$A=\frac{\int_0^{T}\left[1-\frac{\| R(t)-C(t)\|_2}{\| R(t)\|_2}\right]dt}{T'} \tag{8}$$

where, A represents structural fit; $R(t)$ represents the character's limb joint position vector at time t; $C(t)$ represents the position vector of the clothing silhouette's constraint points at the corresponding time; T' represents the total duration of the character's appearance; $\|\cdot\|_2$ represents the Euclidean norm. The craftsmanship dimension encodes brand identity elements into craftsmanship parameters that can be embedded into garment details. A convolutional neural network is used to extract the core features of the brand's visual symbols, generating a craftsmanship symbol vector $V = \{v_1, v_2, \ldots, v_m\}$. v_j represents the feature weight of the j-th craftsmanship symbol, ranging from [0, 1]. The craftsmanship embedding strength is defined as:

$$I = \delta \cdot M_s + \epsilon \cdot S_p + \zeta \cdot P_t \tag{9}$$

where, I represents the craftsmanship embedding strength; M_s represents the material surface recognizability; S_p represents the symbol's proportion in the visual focal area; P_t represents the probability of the craftsmanship detail appearing in close-up shots; δ, ϵ, and ζ represent weight coefficients that sum to one, calculated via a normalization function applied to the dynamic matching score between narrative function and market positioning. The matching degree between the character's narrative function label and the brand's market positioning vector is dynamically calculated.

CHARACTER-BRAND-CLOTHING RETROSPECTIVE VERIFICATION MECHANISM FOR COMMUNICATION CONSISTENCY

The character-brand-clothing retrospective verification mechanism uses multimodal data fusion technology to verify the consistency of design results with the initial goals. Its input sources are clothing design parameter tables and a database of film and television communication samples, and its output is a structured retrospective verification report. This mechanism uses an improved Region-based Convolutional Neural Network (R-CNN) to automatically detect clothing symbols in character appearance sequences and extract key region visual features. The detection process uses a standard sampling rate of 24 frames per second for sequence analysis. The shot boundary is set to the minimum rectangular area covering the entire character's body, and the object detection confidence threshold is uniformly set to 0.85.

The clothing symbol consistency metric is defined as:

$$C_{\text{consistency}} = \frac{1}{N}\sum_{i=1}^{N}\left(1-\frac{\|F_{\text{actual}}(i)-F_{\text{design}}(i)\|_2}{\max\left(\|F_{\text{actual}}(i)\|_2, \|F_{\text{design}}(i)\|_2\right)}\right) \tag{10}$$

where, $C_{\text{consistency}}$ represents the clothing symbol consistency coefficient; N is the total number of clothing symbols detected; $F_{\text{actual}}(i)$ is the actual feature vector of the i-th symbol; $F_{\text{design}}(i)$ is the designed feature vector of the i-th symbol. In cross-platform brand identity element stability analysis, brand visual elements are extracted using a multi-scale Feature Pyramid Network (FPN). The following formula is used to determine the brand symbol stability rate: Cross-platform standardization of visual feature layers, which guarantees feature vector comparability across various resolutions and color gamuts, is the foundation of this computation. The multi-scale FPN network used for feature extraction provides L2-normalized visual embeddings at each feature pyramid level, which are the main input for similarity computations. The similarity function measures the degree of spatial alignment between the features of the reference brand symbol and the detected features of the target platform using this normalized high-dimensional feature space.

$$S_{\text{stability}} = \frac{1}{M}\sum_{j=1}^{M}\frac{1}{K_j}\sum_{k=1}^{K_j}\text{sim}\left(B_{\text{ref}}(k), B_{\text{plat}}(j,k)\right) \tag{11}$$

where, $S_{\text{stability}}$ represents the brand symbol stability rate; M is the total number of communication platforms; K_j is the number of brand symbols detected on the j-th platform; $B_{\text{ref}}(k)$ is the k-th reference brand symbol feature; $B_{\text{plat}}(j,k)$ is the k-th brand symbol feature detected on the j-th platform; $\text{sim}(\cdot,\cdot)$ is the cosine similarity function. The retrospective verification process uses a three-level validation procedure to verify that visual symbols in cross-media communication are semantically consistent, that core brand elements are presented fully, and that character attire and design specifications match. The validation results are quantified using a thorough, weighted scoring model:

$$Q_{\text{retro}} = \alpha_2 C_{\text{consistency}} + \beta_2 S_{\text{stability}} + \gamma_2 R_{\text{semantic}} \tag{12}$$

where, Q_{retro} represents the overall retrospective verification score; α_2, β_2, and γ_2 represent dimension weight coefficients; R_{semantic} represents the semantic consistency index. The validation data is stored in a structured database, forming a retrospective verification table containing key fields such as character number, matching coefficient, and brand symbol stability, providing data support for design optimization.

III. VERIFICATION AND RESULTS OF THE COMMUNICATION EFFECTIVENESS OF THE DESIGN STRATEGY

EXPERIMENTAL DESIGN AND DATA SOURCE

A publicly accessible sample library of motion picture and television productions as well as a brand database provided the experimental data for this investigation. The Internet Archive's Moving Image Library and the Open Media Commons repository, which both offer open-access, copyright-cleared footage under Creative Commons licenses, served as the sources for all the film and television data. Press kits posted on brand websites between 2022 and 2024, annual filings, and official corporate sustainability reports were used to create brand profiles. Script transcripts from the Script Archive Project were compared with character metadata taken from IMDb public datasets. Verifiable public availability, lack of usage restrictions, and conformity to the study's character-brand mapping scope were prerequisites for data inclusion. Using a stratified temporal split, the dataset was divided by year of release to create training, validation, and test subsets while maintaining regional distribution and genre. Operating on Ubuntu 22.04 LTS with CUDA 12.1 and CUDA Deep Neural Network library (cuDNN) 8.9, the computing nodes are outfitted with two Intel Xeon Gold 6348 processors with a combined 56 cores, 128 GB of DDR4 memory, and four NVIDIA A100 GPUs. The Python language processing toolkit, a convolutional neural network training framework, and a semantic analysis module built on the BERT model are among the software dependencies for the Linux operating system.

Before being entered into the database, data sources go through a three-level quality control process that includes integrity checks, feature extraction accuracy verification, and consistency checks for symbolic representations to guarantee the stability and repeatability of further analysis.

High data integrity and consistency were maintained throughout the collection and encoding process of the dataset displayed in Table 4, which includes multi-dimensional information on characters, brands, and footage from films and television shows. Even though brand data offers a trustworthy reference for semantic mapping, the quantity of characters and works from movies and TV shows guarantees diverse sample coverage. The stability of dynamic symbol extraction is guaranteed by the quantity of footage.

TABLE 4. Experimental Dataset Statistics

Data Type	Quantity	Data Quality Indicators
Number of Film and Television Works	120 Films	Data Integrity
Number of Characters	865	Symbolic Consistency
Number of Brands	74	Semantic Mapping Availability
Number of Shot Clips	28,400	Coding Accuracy

Thirty-two fundamental fabric types, including blended materials like polyester and synthetic fibers as well as natural fibers like cotton, linen, silk, and wool, are included in the textile material sample library. Every material's test sample is prepared in accordance with ASTM guidelines, guaranteeing the experimental data's foundation in textile science.

Data collection, character symbol extraction, semantic mapping calculation, and garment design parameter generation are the four stages of the experimental procedure. The data loop is completed by a retrospective verification module, which also ensures that the entire operational framework runs consistently in the experimental setting.

STABILITY OF MATERIAL VISUAL REPRESENTATION IN CROSS-MEDIA ENVIRONMENTS

This study uses empirical data from 28,400 footage clips to systematically analyze the temporal impact of various textile material performance parameters on character representation in order to investigate the dynamic temporal matching between clothing design and character traits in films and television. According to ASTM D1388, the drape coefficient—a crucial measure of a fabric's capacity to hold its shape—is separated into five performance ranges (Group 1: >0.75; Group 2: 0.65–0.75; Group 3: 0.55–0.65; Group 4: 0.45–0.55;

Group 5: <0.45) that correspond to the material's performance in static modeling. Similarly, there are five performance levels for the dynamic deformation index (Group 1: <0.3; Group 2: 0.3–0.4; Group 3: 0.4–0.5;

Group 4: 0.5–0.6; Group 5: >0.6). The temporal correlation mechanism between material properties and character performance is revealed by standardizing the character's appearance into six time intervals and tracking the matching degree of materials in each performance grouping throughout the shot. Figure 3 displays the findings.

Group 2 improves by 0.02 from the beginning, reaching a peak matching degree of 0.95 between 10 and 15 minutes, according to the drape coefficient analysis in Figure 3. The matching degree for Group 1 decreases from 0.97 at the beginning to 0.76 at the end. Group 1 maintains a high matching degree of 0.91–0.95 throughout, with a fluctuation of only 0.04; in contrast, Group 5's matching degree decreases from 0.8 to 0.6, according to dynamic deformation index analysis. The cumulative effect of the characters' dynamic behavior during film and television production is the cause of this data discrepancy. High-drape materials perform well in still photos but become unstable as the amplitude of movement increases. Low-dynamic deformation materials' dense fiber structure allows them to maintain a stable visual appearance during continuous movement. The results provide a quantitative basis based on textile science for clothing design in television and film, demonstrating the importance of matching material characteristics with character performance over time to sustain consistent brand communication.

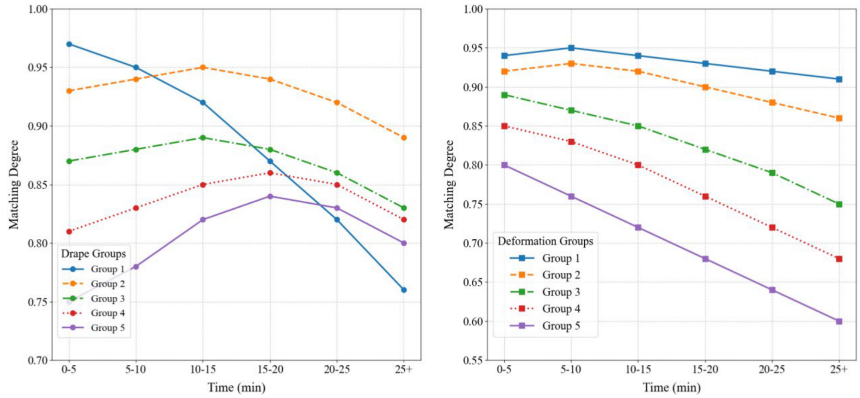

FIGURE 3. Time-Series Variation in Clothing Matching for Different Material Properties during Character Appearances

BRAND SYMBOL RECOGNITION AND CONSISTENCY ASSESSMENT

To investigate the impact of textile material properties and process type on brand symbol recognition in dynamic film and television footage, this study develops a five-level classification system for lens motion intensity based on optical flow analysis and camera trajectory metrics. In terms of brand recognition on cotton and silk, the system methodically assesses the performance of four different processes: jacquard, embroidery, digital printing, and hot stamping. While brand recognition measures how well a brand symbol is recognized in film and television settings, camera motion captures the variety of character movements and the amount of dynamic fabric deformation. These two metrics work together to form the fundamental indicators for assessing process stability.

Notes: The left sub-figure shows the brand recognition performance of different processes on silk; the right sub-figure shows the brand recognition performance of different processes on cotton.

Figure 4 illustrates the structural stability benefit of high-drape coefficient materials under dynamic conditions by showing that the jacquard process on silk maintains a recognition rate of 0.82 during intense motion, which is higher than the 0.66 on cotton. Due to optical interference brought on by the surface's reflective qualities during high-speed motion, the brand symbol recognition rate for the hot stamping process on the silk substrate depicted in the left sub-figure of Figure 4 decreases from 0.91 at rest to 0.68 during intense motion. The smoothness of the fabric surface is crucial for flat printing processes, as evidenced by the low recognition rate of digital prints on cotton during intense motion (0.56), which is 0.32 lower than in the static state. Because of its structural embedding properties, the data show that the jacquard process has the best stability. Consistent brand symbol recognition in dynamic film and television footage is largely dependent on the logical matching of material selection and process type.

VERIFICATION OF THE CORRELATION BETWEEN COLOR STRATEGY AND AUDIENCE PSYCHOLOGICAL PERCEPTION

The relationship between audience psychological perception and the optical characteristics of textile materials has a significant impact on how brand value is communicated in film and television media environments. Silk, linen, cotton, wool, and polyester are the five common textile materials chosen for this study. The color difference patterns are systematically measured under standard illuminants ranging from 2,700 K to 6,500 K. The ΔE value represents the total color difference in the CIELAB color space, while the psychological perception dimensions of warmth, vitality, and refinement were evaluated by a panel of thirty professional costume designers recruited from the industry, using a standardized 7-point Likert scale administered under controlled conditions with prior informed consent obtained. Silk has a high gloss and soft feel; linen exhibits a natural, rugged texture; cotton is moisture-wicking and breathable; wool fibers have a high degree of crimp; polyester exhibits excellent color fastness and stability. By analyzing the relationship between the color performance of materials under standard cinematic lighting and psychological cognition, the mechanism by which the optical properties of textile materials influence the transmission of brand visual symbols is revealed, as shown in Figure 5.

In Figure 5, as the color temperature of the light source increases from 2,700 K to 6,500 K, the ΔE value of wool increases from 2.95 to 6.43, an absolute increase of 3.48 points. However, the ΔE value of polyester only increases from 0.92 to 2.48, an increase of 1.56 points. This is due to the optical property of wool fiber's low reflectivity in the blue spectrum. Wool has a warmth score of 6.7 at 2,700 K and 4.1 at 6,500 K. The decrease in polyester from 4.1 to 2.5 indicates that natural fibers are more vulnerable to changes in the light source's color temperature. Polyester scores 5.8 at 6,500 K, up 1.3 points from 2,700 K, based on vitality data. This lends credence to the psychological theory that cool colors encourage energy. Silk has a delicacy score of 6.5 at 2,700 K and 4.2 at 6,500 K. The relative stability of silk, a luxury fabric, under cold light sources

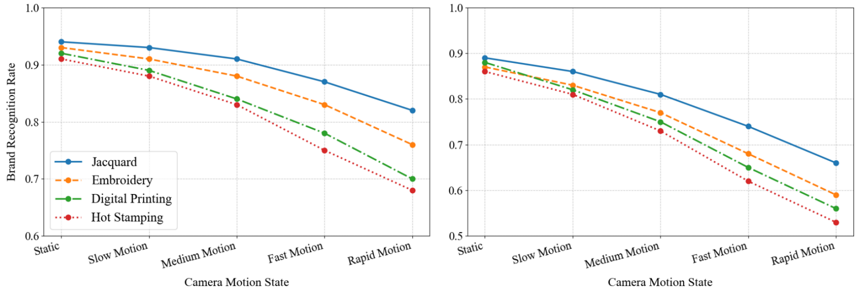

FIGURE 4. Comparison of Dynamic Brand Symbol Recognition Performance Based on Textile Material Properties

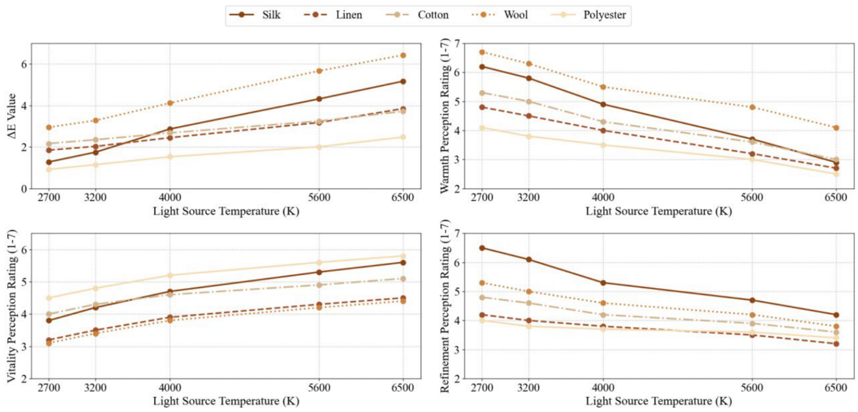

FIGURE 5. Correlation between Textile Color Performance and Psychological Perception under Standard Cinematic Light Sources

is demonstrated by linen's score dropping from 4.2 to 3.2. There is a scientific foundation for color design based on brand positioning in film and television media since research demonstrates that natural fibers have better psychological perceptual qualities under warm light sources, while synthetic fibers retain color stability under cold light sources.

OVERALL CONSISTENCY VERIFICATION OF CLOTHING DESIGN IN CROSS-BORDER COMMUNICATION

This study quantitatively evaluates the semantic consistency of brand visual elements across various platforms by systematically measuring the stability rates of brand symbols for five common textile materials and four core crafts across six mainstream communication platforms using a retrospective verification mechanism. The goal is to investigate the stability characteristics of clothing design elements in film and television works across multimedia communication environments. As seen in Figure 6, the six platforms span the entire media spectrum, from mobile devices to the Digital Cinema Initiatives (DCI)-P3 color gamut in theaters. sRGB stands for Standard Red, Green, and Blue.

The silk material on the cinema platform achieves a stability of 0.95 in Figure 6. It drops to 0.72 for social media short videos as platform resolution decreases, indicating the loss of detail in low-resolution settings brought on by high-gloss materials. Polyester's cross-platform adaptability is demonstrated by its comparatively stable performance across all platforms, with a minimum value of 0.80 that is still higher than that of other natural fibers. Due to its structural embedding properties, which prevent interference from resolution degradation, the jacquard craft achieves a stability of 0.82 on social media short video platforms, which is 0.12 higher than the embroidery craft's 0.70. Just 0.65 stability is attained by the hot stamping craft on social media image platforms, which is 0.28 less stable than on the cinema platform. This is due to excessively enhanced reflective properties in high-contrast environments, leading to symbol distortion. The matching degree between a material's optical properties and platform display parameters directly determines the cross-media consistency of a brand's visual symbol, providing a quantitative basis for fashion brands to develop precise communication strategies.

IV. CONCLUSION

This paper constructs a tripartite semantic mapping framework for film and television character–brand positioning–clothing design. By calculating the weighted cosine similarity between character feature vectors and brand value vectors, this model achieves precise translation of visual symbols in film and television communication. Results show that the matching degree of high-drape materials reaches 0.97 in the initial character stage, validating the supporting role of material properties in static scenes in character expression. The brand symbol stability rate of silk materials on cinema platforms reaches 0.95, exceeding the 0.72 found on social media short video platforms, confirming the crucial influence of matching material optical properties with the display environment on cross-platform communication con-

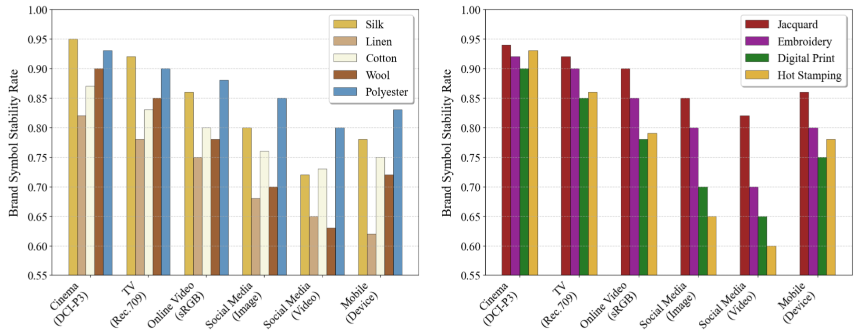

FIGURE 6. Impact of Textile Materials and Crafts on Brand Symbol Stability in Cross-Platform Communication

sistency. By verifying the consistency of design outcomes with initial objectives through a retrospective verification mechanism, this model addresses the lack of a systematic design path for fashion brand film and television communication, providing a quantitative methodology based on textile science for cross-border brand communication, and effectively ensuring the stability and coherence of brand cultural values in visual communication.

AUTHOR CONTRIBUTIONS

Xiaoyue Zhang designed, collected and analyzed the data, and drafted the manuscript. Xiaoyue Zhang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaoyue Zhang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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