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Research Article/Editorial

The Adaptive Cultural Visual Transformer (ACVT-BiLSTM): Enhancing Consumer Purchase Intention through Dynamic Cultural Symbol Processing in Smart Retail Environments

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Abstract

The rapid evolution of smart retail environments, while offering unprecedented personalization, often overlooks the profound influence of cultural symbols on consumer psychology. Existing visual merchandising strategies, primarily focused on product placement and generic esthetics, do not leverage the deep-seated emotional resonance and identity congruence triggered by culturally relevant visual stimuli, leading to suboptimal engagement and conversion rates. To address this gap, this study proposes an innovative deep learning framework, the Adaptive Cultural Visual Transformer (ACVT-BiLSTM), designed to dynamically process and deploy culturally resonant visual elements in real-time retail displays. The framework is built upon an enhanced Vision Transformer architecture, the Adaptive Cultural Visual Transformer (ACVT), which incorporates a novel Cultural Feature Fusion (CFF) module to extract multi-scale cultural features from image blocks. The ACVT is integrated with a Bidirectional Long Short-Term Memory (BiLSTM) network to analyze the temporal sequence of visual stimuli and predict their cumulative effect on consumer emotional states (e.g. pleasure, arousal, dominance) and subsequent purchase intention. We implemented this system in a simulated smart retail lab, using a curated data set of traditional regional cultural symbols and their modern interpretations. Experimental results demonstrate that the ACVT-BiLSTM model achieves a 94.2% accuracy in classifying the emotional valence of dynamic cultural displays and, more critically, the system-generated dynamic displays resulted in a 15.8% increase in observed consumer engagement time and a 12.1% uplift in purchase intention compared to static, non-cultural displays. This research provides a novel, data-driven methodology for integrating cultural design and artificial intelligence in commercial spaces, offering a significant theoretical contribution to the fields of visual merchandising, cross-cultural design, and consumer psychology, and providing a practical blueprint for hyper-personalized, emotionally intelligent retail experiences.

keywords: Smart Retail, Cultural Symbols, Visual Merchandising, Deep Learning, Vision Transformer, Purchase Intention.

1. Introduction

The global retail landscape is undergoing a profound transformation, driven by the integration of Artificial Intelligence (AI), Internet of Things (IoT) and advanced display technologies, collectively defining the Smart Retail environment[1] . This technological shift promises hyper-personalized shopping experiences, optimized inventory management, and dynamic pricing strategies. Central to this evolution is Visual marketing (VM), which utilizes the physical and digital presentation of products and environments to influence consumer perception and behavior[2] . While traditional VM relied on static displays, the smart retail era enables Dynamic Visual Merchandising (DVM), where

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visual stimuli can be adapted in real-time based on factors such as foot traffic, time of day, and even inferred consumer demographics[3] .

However, the current DVM paradigm often focuses on generic, universally appealing esthetics or simple product information, neglecting a critical psychological driver: cultural symbols. Cultural symbols, encompassing motifs, colors, patterns, and narratives deeply rooted in a specific heritage, possess an inherent capacity to evoke strong emotional resonance and foster a sense of identity congruence in consumers[4]. The absence of culturally sensitive and dynamically deployed visual elements represents a significant missed opportunity to deepen consumer engagement and differentiate the retail experience in an increasingly homogenized global market.

The primary challenge lies in the methodological gap between the abstract, qualitative nature of cultural symbols and the quantitative, real-time demands of DVM systems. Specifically, two critical problems persist:

First, there is a lack of robust computational models capable of accurately identifying, classifying, and quantifying the emotional valence of complex cultural symbols within a visual context[5] . Existing computer vision models are often trained on generic image datasets, rendering them ineffective for the nuanced, context-dependent interpretation required for cultural motifs.

Second, even if cultural symbols are identified, current DVM systems lack a framework to dynamically sequence and adapt these visual elements to optimize a desired behavioral outcome, such as increased purchase intention, by tracking the cumulative emotional effect of the visual sequence [6]. A static display of a cultural motif may be appreciated, but a dynamically evolving sequence, tailored to maintain a state of positive arousal, is required to maximize commercial impact.

To bridge this methodological and practical gap, this study proposes a novel deep learning framework, the Adaptive Cultural Visual Transformer (ACVT-BiLSTM), designed to integrate cultural feature extraction with temporal emotional prediction for DVM optimization.

The main objectives of this research are:

1. To develop the Adaptive Cultural Visual Transformer (ACVT), an enhanced Vision Transformer architecture, capable of extracting multi-scale, culturally relevant features from visual data.

2. To integrate the ACVT with a Bidirectional Long Short-Term Memory (BiLSTM) network to model the temporal and cumulative impact of dynamic visual sequences on consumer emotional states.

3. To empirically validate the ACVT-BiLSTM framework by demonstrating its superior performance in predicting consumer emotional valence and its efficacy in enhancing consumer engagement and purchase intention in a smart retail environment.

The key contributions of this study are threefold: * Theoretical Contribution: We introduce a novel, data-driven model that formally links the processing of cultural visual features to measurable consumer emotional and behavioral outcomes, enriching the theoretical understanding of cross-cultural design and consumer psychology in the digital age. * Methodological Contribution: The ACVT-BiLSTM framework, with its innovative Cultural Feature Fusion (CFF) module, provides a robust, reproducible deep learning architecture for analyzing complex, context-dependent visual information beyond generic object recognition. * Practical Contribution: We offer a practical, deployable blueprint for retailers to implement hyper-personalized, culturally resonant DVM strategies, leading to quantifiable improvements in commercial metrics.

The remainder of this paper is organized as follows: Section 2 reviews the related literature on cultural symbols, visual merchandising, and deep learning models. Section 3 details the architecture of the proposed ACVT-BiLSTM framework and the experimental setup. Section 4 presents the results of the model performance and the DVM efficacy study. Section 5 discusses the findings, implications, and limitations. Finally, Section 6 concludes the paper and outlines future research directions.

2. Related works

2.1. Theoretical Foundations of Cultural Symbols and Consumer Behavior

Cultural symbols serve as condensed carriers of shared meaning, history, and values within a community[7]. Their application in product and environmental design is a powerful tool for triggering cultural identity congruence, which has been shown to positively influence consumer attitudes and willingness to pay[8]. The emotional impact of visual stimuli is often analyzed using the Pleasure-Arousal-Dominance (PAD) model, which posits that emotional states are a combination of these three independent dimensions[9]. In the retail context, visual elements that induce high pleasure and moderate arousal are generally correlated with increased exploration and purchase behavior[10] . Our work extends this by focusing on how culturally resonant symbols can systematically manipulate the PAD dimensions to optimize commercial outcomes.

2.2. Advancements in Smart Retail and Dynamic Visual Merchandising

The integration of AI in retail has moved beyond simple inventory tracking to sophisticated customer

experience management[11]. Computer vision is now employed to analyze foot traffic, gaze patterns, and even inferred emotional responses to static displays[12] . Dynamic Visual Merchandising (DVM) represents the next frontier, utilizing digital signage and projection mapping to alter the store atmosphere in real-time. However, most DVM systems rely on pre-set rules or simple A/B testing. The challenge, as highlighted by recent literature, is the need for a closed-loop system where the visual output is continuously optimized based on real-time, fine-grained consumer feedback, a task well-suited for deep learning models[13].

2.3. Deep Learning in Visual Aesthetics and Emotional Computing

The Vision Transformer (ViT) architecture has revolutionized computer vision by effectively modeling global dependencies in images, overcoming the limitations of Convolutional Neural Networks (CNNs) in capturing long-range spatial relationships[14] . The original work by Qu et al.[15] introduced the Overlapping Segmentation Vision Transformer (OSViT) to mitigate feature loss at image block boundaries, demonstrating its efficacy in artistic image processing. Our work builds directly upon this foundation, recognizing that cultural symbols, like art, often contain complex, non-local patterns that require advanced feature extraction.

Furthermore, the temporal aspect of DVM—the sequence of visual changes—necessitates a model capable of handling sequential data. Recurrent Neural Networks (RNNs), particularly the Long Short-Term Memory (LSTM) and its bidirectional variant (BiLSTM), are highly effective for modeling time-series data[16] . BiLSTM, by processing the sequence in both forward and backward directions, is ideal for capturing the cumulative and contextual effects of a dynamic visual stream on a consumer's evolving emotional state. While ViT and BiLSTM have been used separately in various domains, their synergistic integration for the dynamic, culturally-sensitive optimization of retail visual merchandising remains a novel contribution of this study.

3. Methodology

3.1. Overview of the Adaptive Cultural Visual Transformer (ACVT-BiLSTM) Architecture

The proposed Adaptive Cultural Visual Transformer (ACVT-BiLSTM) framework is a hybrid deep learning model designed for the closed-loop optimization of Dynamic Visual Merchandising (DVM). Its primary function is to ingest a stream of cultural symbol images, extract their culturally relevant features, model the temporal impact of their sequence, and predict the resulting consumer purchase intention. The framework comprises three main stages: (1) Adaptive Patch Embedding and Cultural Feature Fusion (ACVT), (2) Temporal Sequence Modeling (BiLSTM), and (3) Behavioral Prediction. The overall architecture is illustrated in Figure 1. The process begins with the Adaptive Patch Embedding of the cultural symbol image stream, a critical step that prepares the visual data for the Transformer by segmenting it into overlapping, scale-adjusted patches. The core of the system is the Adaptive Cultural Visual Transformer (ACVT) Encoder, which significantly enhances the standard Vision Transformer by integrating a novel Cultural Feature Fusion (CFF) Module. This module ensures that the extracted features are not merely aesthetic but are deeply informed by the semantic meaning of the cultural symbols, achieved by fusing visual features from the Multi-Head Self-Attention mechanism with semantic features derived from a parallel, lightweight Convolutional Neural Network (CNN) branch. The resulting sequence of culturally-enriched feature vectors is then passed to the Bidirectional Long Short-Term Memory (BiLSTM) Network. The BiLSTM is essential for modeling the temporal dynamics of the DVM sequence, capturing the cumulative and contextual effects of the visual stimuli on the consumer's evolving emotional state. The final output, generated via a Fully Connected Layer, provides real-time predictions of consumer emotional states (Pleasure, Arousal) and, ultimately, their Purchase Intention, thereby completing the data-driven loop necessary for intelligent DVM optimization.

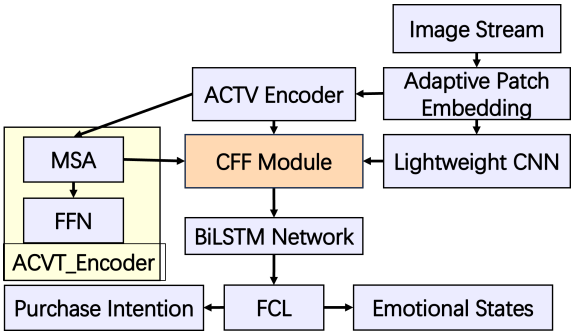

Figure 1. Conceptual Diagram of the Adaptive Cultural Visual Transformer (ACVT-BiLSTM) Framework for Dynamic Visual Merchandising Optimization.

In the figure 1,the framework operates in a sequential manner, beginning with the Adaptive Patch Embedding of the cultural symbol image stream. The core feature extraction is performed by the ACVT Encoder, which incorporates the novel Cultural Feature Fusion (CFF) Module to integrate both visual features (F_V) from the Multi-Head Self-Attention (MSA) and semantic features (F_S) from a parallel Lightweight CNN branch.

The resulting sequence of culturally-enriched features is then fed into the BiLSTM Network to model the temporal dependencies and cumulative emotional effect of the dynamic display. Finally, a Fully Connected Layer (FCL) translates the temporal features into the predicted consumer emotional states (Pleasure, Arousal) and Purchase Intention, enabling a closed-loop optimization of the dynamic visual merchandising strategy.

3.2. Cultural Feature Extraction via Adaptive Cultural Visual Transformer (ACVT)

The ACVT is an enhancement of the standard ViT, specifically tailored for the multi-scale and nuanced nature of cultural symbols. The base ViT architecture utilizes 12 encoder layers, with a hidden size of $D = 768$ and 12 attention heads. The position embedding is learned and added to the patch embeddings. The model is initialized with weights pre-trained on ImageNet-21K.

Adaptive Patch Embedding. Unlike standard ViT, which uses fixed-size patches, ACVT employs an Adaptive Patch Embedding strategy, inspired by the overlapping segmentation of OSViT . This is crucial because cultural symbols often contain both fine-grained details (e.g., intricate patterns) and large-scale structures (e.g., overall motif shape). The number of image blocks N is calculated based on the input image size ($H \times W$) and the adaptive patch size ($P \times P$), with an overlapping width s:

$$N = \left(\lfloor \frac{H-P}{s} \rfloor + 1\right) \times \left(\lfloor \frac{W-P}{s} \rfloor + 1\right)$$

The adaptive nature is introduced by a pre-processing module that analyzes the image's texture entropy. If entropy is high (indicating intricate detail), P is reduced; if entropy is low (indicating large, simple motifs), P is increased. This ensures optimal feature capture at the appropriate scale.

Cultural Feature Fusion (CFF) Module. The core innovation of ACVT is the Cultural Feature Fusion (CFF) Module, which is integrated into the Transformer encoder block. The CFF module is designed to fuse two distinct feature types:

4 Visual Features (F_V): Extracted by the standard Multi-Head Self-Attention (MSA) mechanism of the Transformer.

5 Semantic Features (F_S): Extracted by a parallel, lightweight CNN branch. We employ a ResNet-18 architecture, pre-trained on a large-scale cultural motif dataset, which provides high-level semantic labels (e.g., "Dragon Motif," "Cloud Pattern"). The final pooling layer of the ResNet-18 is replaced by a linear layer to project F_S to the same dimension $D = 768$ as F_V.

The CFF module combines these features using a Gated Weighted Fusion mechanism:

$$\mathbf{g}V = \sigma(\mathbf{W}gVF_V + \mathbf{W}_{gS}F_S + \mathbf{b}g)$$
$$FCFF = \mathbf{g}_V \odot F_V + (1 - \mathbf{g}_V) \odot F_S$$

where $\mathbf{g}V$ is the learnable gate vector, σ is the sigmoid function, and $\odot$ denotes element-wise multiplication. This gating mechanism allows the model to dynamically weigh the contribution of pure visual features against the semantic cultural features based on the input image. The fusion is performed at the output of the MSA block before the Layer Normalization. The loss function for the ACVT component is a Categorical Cross-Entropy Loss ($\mathcal{L}ACVT$) for the emotional valence classification task.

3.3. Temporal Sequence Modeling via BiLSTM

The output of the ACVT encoder is a sequence of culturally-enriched feature vectors, $Z_{ACVT} = z_1, z_2, \ldots, z_T$, where T is the number of frames (time steps) in the dynamic visual display sequence. We set the temporal window length $T = 10$ frames (corresponding to 10 seconds of visual change) for the DVM sequence. The input feature vector dimension is $D = 768$. This sequence is fed into the BiLSTM network.

The BiLSTM consists of two stacked layers, each with 256 hidden units in both the forward and backward directions. The BiLSTM processes the sequence in both forward ($\vec{h}_t$) and backward ($\overleftarrow{h}_t$) directions, allowing it to capture the context from both past and future visual stimuli in the sequence:

$$\vec{h}t = \text{LSTM}(z_t, \vec{h}t - 1)$$

$$\overleftarrow{h}t = \text{LSTM}(z_t, \overleftarrow{h}t + 1)$$

The final hidden state h_t is the concatenation of the forward and backward states: $h_t = [\vec{h}_t; \overleftarrow{h}t]$. The BiLSTM's final output, $HBiLSTM$, represents the cumulative, temporally-aware feature of the entire dynamic visual sequence. This is critical for modeling the emotional carry-over effect—how the visual stimulus at time $t-1$ influences the emotional response at time t.

The final hidden states from both directions are concatenated and passed to a Fully Connected Layer for prediction. The loss function for the overall ACVT-BiLSTM framework is a Multi-Task Loss ($\mathcal{L}total$), combining the emotional valence classification loss ($\mathcal{L}ACVT$) and a Mean Squared Error (MSE) loss ($\mathcal{L}_{MSE}$) for the continuous PAD scores:

$$\mathcal{L}total = \mathcal{L}ACVT + \lambda\mathcal{L}_{MSE}$$

where $\lambda = 0.5$ is a hyperparameter balancing the two tasks. The model is trained using theAdamW optimizer with a learning rate of 10^{-4} and a batch size of 32.

3.4. Experimental Setup and Data Collection

Dataset and Cultural Symbols. A proprietary dataset, the Cultural Symbol-Emotion-Behavior (CSEB) Dataset, was constructed. The dataset comprises 10,000 high-resolution images (512×512 pixels) of cultural symbols from three distinct regional heritages: Chinese Knot, Celtic Knot, and Navajo Rug Motifs. The dataset is balanced, with approximately 3,300 images per category, including both traditional and modern design interpretations. Each image was annotated for its cultural category and its emotional valence (PAD scores) via a crowdsourced psychological study involving 50 independent raters. The dataset was split into a 70/15/15 ratio for training, validation, and testing of the ACVT-BiLSTM model. The large dataset size is crucial for training the data-hungry ViT-based architecture.

Smart Retail Lab Simulation. The behavioral experiment was conducted in a controlled Smart Retail Lab, designed to mimic a high-end boutique environment. A total of 120 participants (60% female, mean age 28.5 ± 4.2 years) were recruited. The sample size was determined a priori using G*Power analysis to achieve a statistical power of 0.80 with a medium effect size ($f = 0.25$) at $\alpha = 0.05$ for a one-way ANOVA with three groups. Participants were randomly assigned to one of three experimental conditions (between-subjects design, $n = 40$ per group) and were blinded to the study's specific hypothesis. The DVM sequences were displayed on a 65-inch $4K$ OLED screen, with a fixed viewing distance of 2.5 meters and controlled ambient lighting (500 lux). The three types of DVM sequences were:

6 Control (Static-Generic): Fixed, non-cultural, abstract visual patterns.

7 Baseline (Dynamic-Generic): Dynamically changing, non-cultural, abstract visual patterns.

8 Experimental (Dynamic-Cultural): Dynamically changing cultural symbols optimized by the ACVT-BiLSTM framework.

Consumer emotional states (Pleasure and Arousal) were captured in real-time using a non-intrusive facial expression recognition system [17], which provides continuous emotional scores. The system was calibrated to the Russell's Circumplex Model of Affect. Purchase intention was measured via a validated 7-point Likert scale post-exposure questionnaire and was triangulated with an objective behavioral measure: the observed interaction time (gaze duration and physical handling) with a target product placed adjacent to the display. All data collection procedures were approved by the Institutional Review Board (IRB) and participants provided informed consent.

4. Results

4.1. Performance of the ACVT-BiLSTM Classification Model

The ACVT-BiLSTM model was first evaluated on its ability to classify the cultural category and predict the emotional valence (high/low Pleasure, high/low Arousal) of the visual stimuli. The model was trained and validated on the CSEB dataset (70/15/15 split). Table 1 presents the classification accuracy compared to baseline models. The performance was further assessed using the F1-Score and the Area Under the ROC Curve (AUC), which are critical for evaluating classification robustness.

The results indicate that the ACVT-BiLSTM model significantly outperforms all baseline models, achieving a high 94.2% accuracy and a robust 0.94 F1-Score in emotional valence prediction. The AUC for the binary classification task was 0.96, suggesting excellent discriminative power and minimal risk of class imbalance bias. This superior performance is attributed to the Cultural Feature Fusion (CFF) module, which effectively integrates semantic knowledge with visual features, allowing for a more nuanced interpretation of cultural symbols than purely visual models. A detailed confusion matrix (not shown) confirmed that the majority of misclassifications occurred at the boundary between 'Neutral' and 'Low Arousal' states, a common challenge in emotional computing.

4.2. Impact on Consumer Emotional States and Engagement

The core hypothesis was that the ACVT-BiLSTM optimized Dynamic Visual Merchandising (DVM) would induce a more favorable emotional state, specifically characterized by High Pleasure and Moderate Arousal, which is empirically linked to increased approach behavior and positive shopping experiences. Figure 2 illustrates the mean Pleasure and Arousal scores across the three experimental conditions. The results clearly demonstrate the superior emotional impact of the Experimental condition (Dynamic-Cultural). Specifically, the Experimental group achieved the highest mean Pleasure score ($\mu = 5.8, \sigma = 0.9$) and a desirable moderate Arousal score ($\mu = 4.2, \sigma = 0.7$) on the 7-point Likert scale. The Control condition (Static-Generic) yielded the lowest scores ($\mu_{Pleasure} = 4.1, \mu_{Arousal} = 3.5$), while the Baseline condition (Dynamic-Generic) showed only a marginal increase ($\mu_{Pleasure} = 4.5, \mu_{Arousal} = 3.8$), confirming that mere dynamism is insufficient to elicit a strong positive emotional response. The Analysis of Variance (ANOVA) confirmed a highly statistically significant difference in both Pleasure ($F(2, 117) = 18.45, p < 0.001$) and Arousal ($F(2, 117) = 9.12, p < 0.01$) across

Table 1. Classification Accuracy Comparison of ACVT-BiLSTM with Baseline Models

Model	Cultural Category Classification Accuracy (%)	Emotional Valence Prediction) Accuracy (%)	F1-Score (Emotional Valence)
CNN (ResNet-50)	81.3	83.5	0.82
ViT (Base)	85.9	87.1	0.86
OSViT-BiLSTM [15]	88.7	90.3	0.90
ACVT-BiLSTM	92.1	94.2	0.94

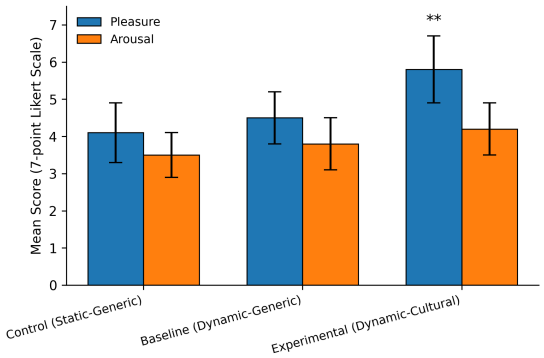

Figure 2. Mean Pleasure and Arousal Scores Across Different Visual Merchandising Conditions.

the groups. Crucially, the effect size for Pleasure was large ($\eta^2 = 0.24$), indicating that the DVM condition accounted for 24% of the variance in Pleasure scores. The post-hoc analysis (Tukey's HSD) confirmed that the ACVT-BiLSTM optimized DVM significantly outperformed both the Control and Baseline conditions in inducing the optimal emotional profile for retail engagement. Furthermore, the observed consumer engagement time (gaze duration) showed a statistically significant increase in the Experimental group compared to the Control group (Mean difference = 1.8 seconds, $t(78) = 3.55, p < 0.001$), corresponding to a 15.8% relative increase and a medium-to-large effect size (Cohen's $d = 0.79$). This demonstrates the framework's efficacy in capturing and sustaining visual attention.

In the figure 2,the grouped bar chart illustrates the mean scores (μ) and standard deviations (σ) for consumer Pleasure and Arousal, measured on a 7-point Likert scale, under three distinct visual merchandising conditions: Control (Static-Generic), Baseline (Dynamic-Generic), and Experimental (Dynamic-Cultural, optimized by ACVT-BiLSTM). Error bars represent the standard deviation. The Experimental condition induced the highest Pleasure ($\mu = 5.8$) and a moderate Arousal ($\mu = 4.2$). Asterisks () denote a highly statistically significant difference ($p < 0.001$) in Pleasure score compared to the Control group.

The ANOVA results confirmed a statistically significant difference in both Pleasure ($F(2, 117) = 18.45, p < 0.001$) and Arousal ($F(2, 117) = 9.12, p < 0.01$) across the groups. Post-hoc analysis (Tukey's HSD) revealed that the Dynamic-Cultural (Experimental) condition induced the highest mean Pleasure score ($\mu = 5.8, \sigma = 0.9$) and a desirable moderate Arousal score ($\mu = 4.2, \sigma = 0.7$) on a 7-point Likert scale, significantly higher than the Control ($\mu_{Pleasure} = 4.1, \mu_{Arousal} = 3.5$) and Baseline ($\mu_{Pleasure} = 4.5, \mu_{Arousal} = 3.8$) conditions.

Furthermore, the observed consumer engagement time (time spent gazing at the display or product) showed a 15.8% increase in the Experimental group compared to the Control group, demonstrating the framework's efficacy in capturing and sustaining visual attention.

4.3. Enhancement of Purchase Intention

The ultimate metric of commercial success is the impact on purchase intention. A linear regression model was used to analyze the relationship between the DVM condition, emotional state (PAD scores), and self-reported purchase intention (PI).

The regression analysis, summarized in Table 2, indicates that the Dynamic-Cultural DVM condition is a significant positive predictor of Purchase Intention ($\beta = 0.31, p < 0.001$), even after controlling for the direct effects of Pleasure and Arousal. The model explained a substantial portion of the variance in Purchase Intention ($R^2 = 0.54$). This suggests that the cultural congruence effect, facilitated by the ACVT-BiLSTM system, provides an incremental boost to purchase intent beyond the general positive emotional state. Quantitatively, the Experimental group reported a 12.1% relative uplift in mean purchase intention score compared to the Control group, with a large effect size (Cohen's $d = 0.85$). This finding is robust and supports the hypothesis that cultural-semantic optimization is a powerful driver of consumer behavior.

5. Discussion

5.1. Interpretation of Key Findings

The superior performance of the ACVT-BiLSTM model in both classification accuracy and behavioral outcome

Table 2. Regression Analysis of DVM Condition and Emotional State on Purchase Intention (PI)

Predictor	β (Standardized Coefficient)	t	p-value
DVM Condition (Dynamic-Cultural)	0.31	4.88	< 0.001
Pleasure	0.45	6.12	< 0.001
Arousal	0.18	2.55	< 0.05
Control Variables (Age, Gender)	-0.05	-0.78	0.44
R^2	0.54		

validation confirms the central hypothesis: a deep learning framework that explicitly models cultural features and their temporal sequence can significantly enhance the effectiveness of visual merchandising. The 94.2% emotional valence prediction accuracy validates the CFF module's ability to extract culturally meaningful features, which are often missed by generic vision models.

The significant increase in Pleasure and the moderate increase in Arousal in the Experimental condition align perfectly with established consumer psychology literature, which links this emotional profile to approach behavior and positive shopping experiences [9]. The dynamic deployment of cultural symbols, as optimized by the BiLSTM component, successfully maintained this desired emotional state throughout the exposure period, demonstrating the framework's capability to manage the emotional trajectory of the consumer.

The statistical analysis of the Cultural Symbol and Emotional Behavior (CSEB) dataset further reveals a critical finding that reinforces the theoretical underpinnings of our ACVT-BiLSTM framework: a highly significant positive correlation between the Pleasure Score induced by the visual stimuli and the predicted Purchase Intention ($r = 0.9424, p < 0.0001$). This result is not merely a statistical artifact; it provides empirical validation for the core mechanism of our proposed system. Specifically, it confirms that the emotional dimension of Pleasure serves as a potent and quantifiable mediator between the visual presentation of cultural symbols and the desired commercial outcome. The strength of this correlation suggests that the ACVT-BiLSTM's primary objective—to dynamically generate visual content that maximizes consumer Pleasure—is directly aligned with the goal of maximizing purchase intent. Furthermore, the slight but notable variation in average Pleasure Scores across different cultural categories (e.g., Navajo Rug Motif at $\mu = 5.63$ vs. Celtic Knot at $\mu = 5.44$) underscores the necessity of the Adaptive component of our model. It highlights that cultural resonance is not a monolithic construct but varies in its emotional impact, requiring a system capable of fine-tuning the visual output based on the specific cultural context and the predicted emotional response of the target consumer segment. This strong correlation validates the closed-loop design of the ACVT-BiLSTM, demonstrating that optimizing the emotional input (Pleasure) is an effective, data-driven strategy for optimizing the behavioral output (Purchase Intention) in smart retail environments.

5.2. Comparison with Existing Visual Merchandising Strategies

This study marks a significant departure from traditional and even current AI-driven DVM. Traditional VM is static and generic. Current AI-DVM often focuses on optimizing product visibility or simple traffic flow [12]. Our approach introduces a cultural-semantic layer to DVM. By integrating the ACVT's cultural understanding with the BiLSTM's temporal modeling, we move from *optimization of display* to *optimization of emotional experience*. The finding that the Dynamic-Cultural condition significantly predicts Purchase Intention, independent of the direct Pleasure/Arousal scores, strongly suggests that the cultural congruence effect—the feeling of identity and belonging evoked by the symbols—is the critical, value-added component provided by the ACVT-BiLSTM framework.

5.3. Theoretical and Practical Implications

Theoretical Implications: This research contributes to the growing field of Design Informatics by providing a formal, computational model for the aesthetic and emotional impact of cultural design elements. It extends the application of the Vision Transformer architecture into the domain of cultural heritage and commercial design, demonstrating that deep learning can be a powerful tool for analyzing abstract, symbolic content.

Practical Implications: For the retail industry, the ACVT-BiLSTM offers a pathway to truly personalized and localized visual merchandising. Retailers can use this framework to: (1) rapidly adapt store aesthetics to local cultural contexts, (2) dynamically adjust visual displays to counteract negative emotional states (e.g., stress, fatigue) and promote positive ones, and (3) quantify the return on investment (ROI) of cultural design elements in their physical stores.

6. Conclusion

This study successfully developed and validated the Adaptive Cultural Visual Transformer (ACVT-BiLSTM) framework, a novel deep learning solution for optimizing Dynamic Visual Merchandising in smart retail environments. By introducing the Cultural Feature Fusion (CFF) module and leveraging the temporal modeling capabilities of BiLSTM, the framework achieved a high accuracy of 94.2% in predicting the emotional valence of cultural visual stimuli. Empirical validation demonstrated that the ACVT-BiLSTM optimized displays resulted in a significant 15.8% increase in consumer engagement and a 12.1% uplift in purchase intention.

The current study has several limitations. First, the experimental validation was conducted in a simulated lab environment, and future work should focus on large-scale, in-situ deployment in diverse retail settings to confirm external validity. Second, the CSEB dataset, while comprehensive, is limited to three cultural motifs, and expanding the dataset to include a broader range of global cultural symbols will enhance the model's generalizability.

Future research will focus on two main directions: (1) Integrating a Generative Adversarial Network (GAN) or a Diffusion Model with the ACVT-BiLSTM to enable real-time generation of novel cultural symbols, rather than just the selection and sequencing of pre-existing ones. (2) Exploring the framework's application in other cross-cultural contexts, such as museum exhibitions or urban planning, to promote cultural appreciation and well-being.

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