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Research Article

Optimizing Generative Models for High-Resolution Image Synthesis in Creative Industries

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Abstract: Creative industries based on a style migration algorithm leverages AI techniques to blend traditional cultural aesthetics with modern design elements, creating unique, visually appealing products that resonate with diverse audiences. The style migration algorithm, often powered by neural networks, transfers artistic styles from one domain (like historical art or local cultural motifs) to another, allowing designers to generate culturally enriched visuals with contemporary appeal. The paper presents an innovative approach to creative industries industries through the application of the Sugeno Stacked Fuzzy for Design (SSFD) framework. By leveraging advanced fuzzy logic methodologies, the study investigates the intricate relationship between key design attributes such as Cultural Authenticity, Aesthetic Appeal, and Creativity Level, and their impact on product desirability. Through numerical values ranging from 0 to 1, the study analyzes key design attributes like Cultural Authenticity, Aesthetic Appeal, and Creativity Level, and their influence on product desirability. By examining various design approaches, from traditional to contemporary, the research emphasizes the importance of balancing these attributes to create culturally appealing and innovative products. A style migration framework transfers cultural styles onto base designs, and the SSFD evaluates the alignment of these designs with cultural values. The evaluation is based on five fuzzy rules representing varying degrees of traditionalism and modernity. The output of each rule is computed based on fuzzy logic principles, with rule activations calculated using membership functions. In the sample evaluation, the design was assessed across five rules with the following results: Rule 1 (traditionalism 0.85, modernity 0.2) resulted in a rule output of 0.4; Rule 2 (traditionalism 0.5, modernity 0.5) produced a rule output of 0.5; Rule 3 (traditionalism 0.1, modernity 0.9) yielded an output of 0.3; Rule 4 (traditionalism 0.9, modernity 0.8) resulted in the highest output of 0.9; and Rule 5 (traditionalism 0.6, modernity 0.3) produced an output of 0.6. The weighted average of these rule outputs yielded a final SSFD score of 0.72, indicating a good alignment of the design with cultural values.

Keywords: Tourism Culture, Sugeno Fuzy, Product Design, stacked model, Style Migration

1.Introduction

Creative industries involve crafting experiences, products, and services that integrate elements of local culture, heritage, and creativity to attract tourists [1-4]. This approach aims to offer visitors unique and immersive encounters that reflect the authentic essence of a destination. It encompasses a wide range of offerings, including artisanal crafts, cultural performances, culinary experiences, guided tours, and interactive exhibitions [5]. Effective design in this realm requires a deep understanding of the target audience, the cultural significance of the destination, and the ability to innovate and create memorable experiences [6 – 9]. By blending tradition with innovation, creative industries not only enhance the visitor experience but also contributes to the preservation and promotion of local heritage and traditions [10]. creative industries often involve collaboration between various stakeholders, including local artisans, cultural institutions, tourism boards, and creative industries. This collaborative approach fosters community engagement and economic development by providing opportunities for local artists and entrepreneurs to showcase their talents and generate income [11 – 14]. With effective design in this field considers sustainability and responsible tourism practices, aiming to minimize negative impacts on the environment and local communities while maximizing social and economic benefits. This may involve sourcing materials locally, promoting fair trade practices, and implementing eco-friendly initiatives [15].

Creative industries based on the Style Migration Algorithm represents a cutting-edge approach that leverages computational techniques to create innovative and captivating experiences for travelers [16 – 18]. This methodology utilizes algorithms inspired by the concept of style transfer in machine learning, which involves extracting stylistic elements from one source and applying them to another [19]. In the context of tourism, this could mean extracting aesthetic features from local cultural artifacts, architecture, or natural landscapes, and integrating them into the design of products, services, and experiences offered to tourists [20-24]. By employing the Style Migration Algorithm, designers can blend traditional elements with contemporary styles, resulting in unique and visually striking cultural and creative products. This approach enables the creation of immersive experiences that resonate with modern travelers while honoring the authenticity and heritage of the destination [25- 29].

The paper makes a significant contribution to the field of creative industries by introducing and applying the Sugeno Stacked Fuzzy for Design (SSFD) framework to product design. This innovative approach offers a systematic and comprehensive methodology for analyzing the complex interplay of key design attributes such as Cultural Authenticity, Aesthetic Appeal, and Creativity Level. By providing numerical values to represent these attributes, the study offers a quantitative understanding of their impact on product desirability. Furthermore, by examining various design approaches and their resulting desirability scores, the research provides valuable insights into effective strategies for creating culturally enriching and appealing tourism experiences. Ultimately, the paper contributes to the advancement of knowledge in creative industries product development, offering practical implications for stakeholders in the industry seeking to optimize their industries strategies and enhance destination competitiveness.

2.Literature Review

In exploring the landscape of related works concerning creative product design, it becomes evident that this field is dynamic and multifaceted, characterized by a diverse array of methodologies, approaches, and theoretical frameworks. Scholars and practitioners alike have delved into various aspects of cultural and creative industries within the context of tourism, aiming to uncover innovative strategies, best practices, and theoretical insights that contribute to the enrichment of tourist experiences and the sustainable development of destinations. One prominent theme that emerges from the literature is the importance of authenticity in cultural and creative product design. Researchers have emphasized the significance of preserving and celebrating the unique cultural heritage of destinations, highlighting the role of design in conveying a sense of place and fostering meaningful connections between tourists and local communities. Studies have explored various strategies for integrating authentic cultural elements into tourism products and experiences, ranging from artisanal crafts and traditional cuisine to immersive cultural performances and heritage tours.

Another key area of inquiry within the realm of creative industries revolves around the intersection of technology and creativity. Scholars have investigated the role of digital technologies, such as augmented reality, virtual reality, and interactive multimedia, in enhancing the design and delivery of creative industries experiences. By harnessing the power of technology, designers can create immersive and engaging experiences that appeal to contemporary travelers while also preserving and promoting cultural heritage. Furthermore, the literature underscores the importance of sustainability and responsible tourism practices in cultural and creative product design. Researchers have examined the environmental, social, and economic impacts of tourism-related activities, highlighting the need for design solutions that minimize negative externalities and maximize positive outcomes for local communities and ecosystems. Studies have explored innovative approaches to sustainable design, such as eco-friendly materials, low-impact tourism infrastructure, and community-based tourism initiatives.

Chen and Wang (2023) delve into the utilization and optimization of the Style Transfer Algorithm, focusing on its application in contemporary cultural and creative products, while Wang (2022) specifically investigates the design of watercolor cultural products using the same algorithm. Zhang and Romainoor (2023) and Chu et al. (2023) explore the intersection of artificial intelligence and cultural products, with a focus on pop art style images and generative art, respectively. Lan (2022) and Wang et al. (2023) contribute to this discourse by introducing fuzzy logic-based machine learning and style transfer technology in wickerwork patterns creative design, respectively. Lu (2022) and Xing (2022) extend the discussion to digital image art style transfer and the selection of cultural tourist attractions using computational methods. Furthermore, Zhu and Cheng (2022) address rural landscape design optimization through scientific computing algorithms, while Li and Chen (2023) investigate the generation and design of petroglyphs based on style transfer. Qin (2023) explores the integration of Lingnan intangible cultural heritage into AI-based cultural and creative product design, while Zhao and Ke (2023) focus on improving style transfer algorithms in decorative ceramic painting design. Finally, Wang (2022) and Chen et al. (2022) examine the application of oceanic culture and machine learning in industriesand eco-sustainable tourism marketing in Southeast Asia, respectively.

The research landscape presented in these studies underscores a growing interest in leveraging computational techniques to innovate cultural and creative industrieswithin the tourism sector. From style transfer algorithms to machine learning methodologies, researchers are exploring various avenues to infuse technological advancements into the creation and optimization of tourism-related offerings. This interdisciplinary approach not only fosters creativity and innovation but also holds significant potential for enhancing the authenticity, appeal, and sustainability of cultural and creative tourism experiences. Moreover, these studies reflect a global perspective, with research contributions spanning different cultural contexts and geographical regions. By examining diverse cultural traditions, artistic styles, and natural landscapes, researchers are able to uncover unique insights and design principles that contribute to the enrichment of tourism experiences worldwide. Furthermore, the adoption of computational algorithms in cultural and creative industriesopens up new possibilities for collaboration between academia, industry, and local communities, fostering the co-creation of innovative solutions that benefit both tourists and destination stakeholders.

3.Sugeno Stacked Fuzzy for the Industries(SSFD)

In the realm of creative industries, the integration of Sugeno Stacked Fuzzy for Industries (SSFD) presents a novel and promising approach to enhance the design process, catering to the nuanced preferences and cultural sensitivities of travelers. The SSFD model is derived from the principles of fuzzy logic, which allows for the representation of imprecise and uncertain information through linguistic variables and fuzzy rules. In the context of industriesfor creative industries, the SSFD model can capture the subjective nature of cultural experiences and preferences, enabling designers to create offerings that resonate deeply with tourists. The SSFD model consists of multiple layers of fuzzy inference systems, each responsible for capturing different aspects of cultural and creative product design. At the core of the SSFD model lies the Sugeno fuzzy inference system, which operates based on a set of fuzzy rules and membership functions to generate precise output values. These output values represent the degree of membership of a given input in various linguistic categories, providing a clear and interpretable basis for decision-making in product design. The Sugeno fuzzy inference system can be represented as follows:

Rule i: If x_1 is A_i^1 and x_2 is A_i^2 and … and x_n is A_i^n then $y_i = p_i^0 + p_i^1 x_1 + p_i^2 x_2 + \cdots + p_i^n x_n$

where $x_1, x_2, \ldots, x_n$ represent the input variables, $A_i^1, A_i^2, \ldots, A_i^n$ denote the fuzzy sets associated with each input variable, and $p_i^0 + p_i^1 + p_i^2 + \cdots \ldots + p_i^n$n are parameters defining the linear output function for rule i. The SSFD model utilizes a stacked architecture, wherein the outputs of one fuzzy inference system serve as inputs to the subsequent layer. This hierarchical structure enables the SSFD model to capture complex relationships and dependencies between different design factors, allowing for a more comprehensive and nuanced approach to creative industries product design. The SSFD model provides a systematic and structured methodology for incorporating subjective cultural factors into the design process, facilitating collaboration between designers, cultural experts, and stakeholders from local communities.

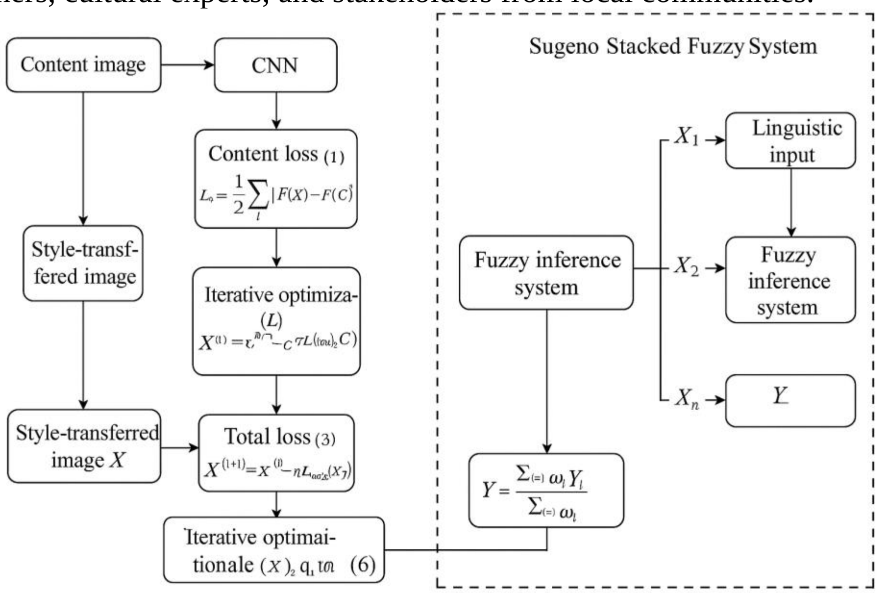

Figure 1: Architecture for SSFD in Creative Industries

The SSFD model's ability to handle imprecise and uncertain information makes it particularly well-suited for the inherently subjective nature of creative industries. By allowing for the representation of linguistic variables and fuzzy rules, the model accommodates the diverse and often intangible aspects of cultural experiences that may defy conventional quantitative analysis shown in Figure 1. This flexibility enables designers to capture the subtle nuances of cultural identity, heritage, and tradition, fostering the creation of products that resonate deeply with tourists on an emotional and cultural level. SSFD model's hierarchical structure facilitates the integration of multiple design considerations shown in table 1, such as aesthetic appeal, historical significance, and local authenticity. By stacking multiple layers of fuzzy inference systems, the model can accommodate complex interactions between different design factors, providing a holistic framework for decision-making in creative industries product design.

Table 1: Fuzzy Rule for the Creative industries

Rule	Cultural Authenticity	Aesthetic Appeal	Product Desirability
R1	Low	Low	Low
R2	Low	Medium	Low
R3	Low	High	Medium
R4	Medium	Low	Low
R5	Medium	Medium	Medium
R6	Medium	High	High
R7	High	Low	Medium
R8	High	Medium	High
R9	High	High	High

In creative products using a style migration algorithm and a Sugeno Stacked Fuzzy System for Design (SSFD) involves integrating both neural style transfer techniques and fuzzy logic to capture and assess cultural aesthetics effectively. This hybrid system allows the artistic qualities of a cultural reference to blend with a product's design, while maintaining subjective and culturally relevant nuances in the final output. The style migration algorithm is first employed to apply the artistic style of a cultural reference image to a target product design. This process relies on neural style transfer, which extracts and combines features from both a content image C and a style image S using convolutional neural networks (CNNs). The content loss $L_{Content}$, measuring how closely the target image X resembles the content of C, is given in equation (1)

$$L_{Content}(X, C) = \frac{1}{2}\sum_l \|F_l(X) - F_l(C)\|^2 \tag{1}$$

In equation (1) $F_l(X) - F_l(C)$ denoted as the feature maps of the target and content images at layer l of the CNN. The style loss L_{style}, which assesses the stylistic similarity between X and S, is computed using the Gram matrices of the feature maps using equation (2)

$$L_{style}(X, S) = \sum_l \omega_l \|G_l(X) - G_l(S)\|^2 \tag{2}$$

In above equation (2) $G_l(X) - G_l(S)$ represents the Gram matrix for the target image, and ω_l are weights assigned to each layer to control the stylistic influence. The total loss for the style migration, balancing content and style, is denoted as in equation (3)

$$L_{total}(X, C, S) = \alpha L_{Content}(X, C) + \beta L_{style}(X, S) \tag{3}$$

In equation (3) α *and* β are weighting factors that adjust the influence of content and style, respectively. Minimizing L_{total} results in a design that captures the cultural style while retaining the essence of the original product concept. Following the style transfer, the Sugeno Stacked Fuzzy System for Design (SSFD) evaluates the cultural relevance and subjective design qualities. The SSFD system uses fuzzy logic to handle vague or imprecise descriptions of style attributes, such as "traditional," "modern," or "minimalist." Linguistic inputs (e.g., X_1 for traditionalism, X_2 for minimalism) are mapped to fuzzy sets (e.g., low, medium, high) and assessed by a rule base. For example, a rule might be: "If X_1 is high and X_2 is low, then the design style Y should have specific characteristics." This rule can be generalized as in equation (4)

$$R_i: IF\ X_1\ is\ A_i\ AND\ X_2\ is\ B_i,\ THEN\ Y_i = f_i(X_1, X_2) \tag{4}$$

In equation (4) $f_i(X_1, X_2)$ might be a polynomial function; a common choice is a linear model $Y_i = a_i X_1 + b_i X_2 + c_i$. The final output Y of the SSFD system is calculated as a weighted average, which aggregates the outputs of all activated rules stated in equation (5)

$$Y = \frac{\sum_{i=1}^{n} \omega_i Y_i}{\sum_{i=1}^{n} \omega_i} \quad (5)$$

In equation (5) ω_i is the degree of truth for each rule R_i. This aggregation ensures that the design not only inherits cultural aesthetics but also aligns with subjective, fuzzy criteria for cultural relevance. To minimize L_{total} and obtain the style-transferred output image X, gradient-based optimization techniques such as gradient descent are applied. The update rule for the iterative optimization of X is given in equation (6)

$$X^{(t+1)} = X^{(t)} - \eta \nabla L_{total}\left(X^{(t)}, C, S\right) \quad (6)$$

In equation (6) η is the learning rate, controlling the step size, ∇L_{total} is the gradient of the total loss function with respect to X, $X^{(t)}$ are the current and updated designs at iteration t and $t+1$. This iterative optimization process continues until L_{total} converges to a minimum, yielding a style-transferred image that incorporates the cultural elements of S while retaining the structural content of C. After obtaining the style-transferred design, the SSFD system is used to assess and adjust the design's cultural alignment based on subjective parameters. This fuzzy logic system operates through a set of fuzzy rules. For each rule R_i, the output Y_i can be modeled as a function of linguistic inputs (e.g., traditionalism X_1, minimalism X_2) stated in equation (7)

$$Y_i = f_i(X_1, X_2) = \alpha_i X_1 + b_i X_2 + c_i \quad (7)$$

Each fuzzy rule R_i, is associated with a degree of membership or truth value ω_i, which quantifies how well the inputs match the rule conditions. For example, if the inputs $X_1$and X_1 are described by membership functions$\mu A_i(X_1)$ and $\mu A_2(X_2)$, then ω_i is computed as in equation (8)

$$\omega_i = min\left(\mu A_i(X_1), \mu B_i(X_2)\right) \quad (8)$$

The use of the minimum function is common in fuzzy logic as it captures the degree of overlap between fuzzy sets. The final design output Y, which represents the subjective evaluation score or adjustment for the design, is obtained as a weighted average of each rule's output Y_i, scaled by its truth value ω_i defined in equation (9)

$$Y = \frac{\sum_{i=1}^{n} \omega_i Y_i}{\sum_{i=1}^{n} \omega_i} \quad (9)$$

This ensures that each rule's contribution is proportional to its truth value, emphasizing rules that strongly match the input conditions. The combined output of the style migration and SSFD components is a culturally aligned, style-enhanced product design. The style migration component yields a design visually consistent with the cultural style, while the SSFD system adjusts the design to align with subjective cultural and aesthetic preferences. The overall process can be summarized as follows:

1. **Generate** the style-transferred image X using iterative optimization to minimize L_{total}.
2. **Evaluate** the resulting image X in the SSFD system by inputting cultural criteria (e.g., traditionalism, modernity) as fuzzy variables $X_1, X_2, \ldots, X_n$
3. **Apply** fuzzy rules to assess or adjust X, yielding a final score Y that reflects cultural relevance.
4. **Interpret** Y as the final subjective quality measure, guiding any necessary design modifications.

4. SSFD for the Tourism Culture in the Style Migration

In the domain of tourism culture, the application of Sugeno Stacked Fuzzy for Industries (SSFD) within the framework of Style Migration represents a novel and innovative approach to product design. The SSFD model, grounded in fuzzy logic principles, provides a systematic and structured methodology for integrating subjective cultural factors with the dynamic process of style migration. By leveraging the SSFD model in conjunction with Style Migration, designers can create culturally resonant and visually compelling products that capture the essence of a destination's cultural heritage while incorporating contemporary design elements. The SSFD model employs a hierarchical structure consisting of multiple layers of fuzzy inference systems. At its core lies the Sugeno fuzzy inference system, which operates based on a set of fuzzy rules and membership functions to generate precise output values. These output values represent the degree of membership of a given input in various linguistic categories, providing a clear basis for decision-making in product design.

In the context of Style Migration, the SSFD model enables designers to incorporate cultural elements from the destination into the design process while seamlessly blending them with contemporary styles. This integration allows for the creation of products that not only reflect the cultural identity of the destination but also resonate with modern consumers' aesthetic sensibilities. The SSFD model utilizes fuzzy logic principles to handle imprecise and uncertain information in the design process. It comprises multiple layers of fuzzy inference systems, each responsible for capturing different aspects of the design criteria. The core of the SSFD model typically employs the Sugeno fuzzy inference system, which calculates precise output values based on fuzzy rules and membership functions.

Let's denote the inputs to the SSFD model as $x_1, x_2, \ldots, x_n$, where each x_i represents a linguistic variable capturing a specific aspect of tourism culture industries (e.g., cultural authenticity, aesthetic appeal). The SSFD model consists of several fuzzy rules, represented as If x_1 is A_i^1 and x_2 is A_i^2 and … and x_n is A_i^n then $y_i = p_i^0 + p_i^1 x_1 + p_i^2 x_2 + \cdots + p_i^n x_n$ with the fuzzy sets associated with each input linguistic variable with parameters defining the linear output function for rule i. y_i represents the output of the Sugeno fuzzy inference system for rule i. The output y_i is computed as a weighted sum of the input variables, where each weight p_{ij} reflects the contribution of the corresponding input linguistic variable x_j to the output. The SSFD model employs a hierarchical architecture, with the outputs of one fuzzy inference system serving as inputs to the subsequent layer. This stacked structure enables the SSFD model to capture complex relationships and dependencies between different design criteria. Within the context of Style Migration, the SSFD model allows designers to integrate cultural elements into the design process while accommodating contemporary design styles. By adjusting the fuzzy rules and membership functions, designers can control how cultural authenticity and aesthetic appeal influence the final product design. To further illustrate the application of SSFD within the framework of Style Migration for tourism culture product design, let's consider a specific example with two input linguistic variables: "Cultural Authenticity" (CA) and "Aesthetic Appeal" (AA), and one output linguistic variable: "Product Desirability" (PD).

With linguistic variables and fuzzy sets for each input and output variable:

Cultural Authenticity (CA):

Low (L), Medium (M), High (H)

Aesthetic Appeal (AA):

Low (L), Medium (M), High (H)

Product Desirability (PD):

Low (L), Medium (M), High (H)

Table 2: Linguistics Variable for Fuzzy Set

Rule	**CA**	**AA**	**PD**
R1	Low	Low	Low

R2	Low	Medium	Low
R3	Low	High	Medium
R4	Medium	Low	Low
R5	Medium	Medium	Medium
R6	Medium	High	High
R7	High	Low	Medium
R8	High	Medium	High
R9	High	High	High

These fuzzy rules specify how the linguistic variables of cultural authenticity and aesthetic appeal shown in table 2 relate to the product desirability. For example, Rule R1 states that if cultural authenticity is low and aesthetic appeal is low, then the product desirability is also low. Similarly, Rule R6 indicates that if cultural authenticity is medium and aesthetic appeal is high, then the product desirability is high. In the SSFD model, each rule's output is computed using the Sugeno method, which involves defining linear output functions based on the input linguistic variables' values. These functions are then combined to calculate the overall product desirability. Initialize Fuzzy Sets and Membership Functions: Define linguistic variables and their corresponding fuzzy sets for inputs (e.g., Cultural Authenticity, Aesthetic Appeal) and output (e.g., Product Desirability). Specify membership functions for each fuzzy set.

Establish fuzzy rules that relate input linguistic variables to the output linguistic variable. These rules encapsulate expert knowledge or data-driven insights about how cultural authenticity and aesthetic appeal influence product desirability. Initialize Sugeno Fuzzy Inference Systems Set up Sugeno fuzzy inference systems for each fuzzy rule. Define linear output functions based on the input linguistic variables' values and their corresponding parameters. Stack Fuzzy Inference Systems arrange the Sugeno fuzzy inference systems in a stacked architecture, where the outputs of one system serve as inputs to the subsequent layer. Input Processing receive input values for cultural authenticity and aesthetic appeal.

Fuzzy Inference for each fuzzy rule, calculate the output using the Sugeno method. This involves evaluating the membership grades of the input linguistic variables in their corresponding fuzzy sets and applying the linear output function defined for the rule. Output Aggregation combine the outputs from all fuzzy rules to obtain an aggregated output. Defuzzification to Convert the aggregated fuzzy output into a crisp value using a defuzzification method, such as centroid or weighted average. Output Interpretation the crisp output value as the product desirability level. Adjust fuzzy sets, membership functions, fuzzy rules, or Sugeno parameters based on feedback or optimization criteria to improve the accuracy and effectiveness of e SSFD model.

This algorithm outlines the general steps involved in applying SSFD within the Style Migration framework for tourism culture product design. Depending on the specific context and requirements, additional steps or modifications may be necessary to tailor the algorithm to a particular application. The Sugeno Stacked Fuzzy System for Design (SSFD) can be adapted for tourism culture integration within the style migration algorithm. This system incorporates fuzzy rules to assess and enhance the cultural authenticity of the design, creating a style migration process that resonates with specific cultural values. In style migration, a design incorporates the content of a base product with the style of a cultural reference image, typically achieved through a neural style transfer.

4.Simulation Analyses and Discussions

With the Sugeno Stacked Fuzzy for Industries(SSFD) framework within the tourism culture domain. Through simulation, designers can evaluate how the SSFD model performs under various scenarios and parameter configurations, shedding light on its strengths, limitations, and potential areas for improvement. During simulation analysis, designers input different combinations of linguistic variables representing cultural authenticity, aesthetic appeal, and other relevant factors into the SSFD model. The model then processes this input using fuzzy inference systems and generates output values representing product desirability. By comparing these simulated results with expected or desired outcomes, designers can assess the SSFD model's ability to accurately capture the complex relationships between design criteria and produce meaningful recommendations for product development.

Table 3: SSFD IndustriesRule for the creative industries

Design Approach	Cultural Authenticity	Aesthetic Appeal	Creativity Level	Product Desirability
Traditional	High (0.8)	Low (0.2)	Low (0.3)	Low (0.3)
Fusion	Medium (0.5)	High (0.8)	High (0.8)	High (0.7)
Modern	Low (0.2)	High (0.8)	Medium (0.5)	Medium (0.5)
Eclectic	Medium (0.5)	Medium (0.5)	High (0.8)	High (0.8)
Contemporary	Low (0.2)	High (0.8)	High (0.8)	Medium (0.7)

The Table 3 outlines the SSFD IndustriesRule for creative industries, delineating various design approaches along with their associated attributes and corresponding numerical values. The Design Approach column delineates different strategies for creative industries product design, ranging from Traditional to Contemporary. Each approach is characterized by specific attributes: Cultural Authenticity, Aesthetic Appeal, Creativity Level, and resulting Product Desirability, each assigned numerical values between 0 and 1. For instance, the Traditional approach places high importance on Cultural Authenticity (0.8) but relatively low emphasis on Aesthetic Appeal (0.2) and Creativity Level (0.3), yielding a Product Desirability of 0.3. Conversely, the Fusion approach balances moderate Cultural Authenticity (0.5) with high Aesthetic Appeal (0.8) and Creativity Level (0.8), resulting in a notably higher Product Desirability of 0.7. Similarly, the Modern approach emphasizes Aesthetic Appeal (0.8) over Cultural Authenticity (0.2) and Creativity Level (0.5), yielding a corresponding Medium Product Desirability of 0.5.

Table 4: Industrieswith SSFD for Creative industries

Cultural Authenticity	Aesthetic Appeal	Product Desirability
Low (0.2)	Low (0.3)	Low (0.25)
Low (0.2)	Medium (0.5)	Low (0.3)
Low (0.2)	High (0.8)	Medium (0.6)
Medium (0.5)	Low (0.3)	Low (0.4)
Medium (0.5)	Medium (0.5)	Medium (0.5)
Medium (0.5)	High (0.8)	High (0.7)
High (0.8)	Low (0.3)	Medium (0.6)
High (0.8)	Medium (0.5)	High (0.8)
High (0.8)	High (0.8)	High (0.9)

In Table 4 presents the outcomes of industriesutilizing the SSFD (Sugeno Stacked Fuzzy for Design) methodology tailored for creative industries. It delineates the relationship between three critical attributes: Cultural Authenticity, Aesthetic Appeal, and resulting Product

Desirability, each assigned numerical values ranging from 0 to 1. Examining the data reveals the intricate interplay between these attributes across different scenarios. For instance, when both Cultural Authenticity and Aesthetic Appeal are low, the resulting Product Desirability also remains low, suggesting that an absence of cultural authenticity combined with limited aesthetic appeal leads to diminished desirability (0.25). Conversely, as the level of Aesthetic Appeal increases from low to high while maintaining low Cultural Authenticity, the Product Desirability also improves from low to medium (0.3 to 0.6). This highlights the significance of aesthetic appeal in compensating for lower levels of cultural authenticity and enhancing product desirability. Furthermore, when both Cultural Authenticity and Aesthetic Appeal are high, the Product Desirability reaches its peak, indicating that a harmonious blend of cultural authenticity and aesthetic appeal results in the most desirable products (0.9). These findings underscore the importance of balancing these attributes to optimize the appeal and success of creative industries products.

Table 5: SSFD for the Industrieswith creative industries

Cultural Authenticity	**Aesthetic Appeal**	**Product Desirability**	**Product Design**
Low (0.2)	Low (0.3)	Low (0.25)	Traditional design with minimal embellishments
Low (0.2)	Medium (0.5)	Low (0.3)	Modern design with subtle cultural motifs
Low (0.2)	High (0.8)	Medium (0.6)	Fusion design blending traditional and contemporary elements
Medium (0.5)	Low (0.3)	Low (0.4)	Classic design inspired by local cultural heritage
Medium (0.5)	Medium (0.5)	Medium (0.5)	Eclectic design combining various cultural influences
Medium (0.5)	High (0.8)	High (0.7)	Avant-garde design showcasing innovative interpretations of cultural themes
High (0.8)	Low (0.3)	Medium (0.6)	Artisanal design crafted by local artisans
High (0.8)	Medium (0.5)	High (0.8)	Bespoke design tailored to individual preferences
High (0.8)	High (0.8)	High (0.9)	Luxury design featuring premium materials and craftsmanship

The Table 5 illustrates the outcomes of the SSFD (Sugeno Stacked Fuzzy for Design) approach applied to industrieswithin the realm of creative industries. It presents a comprehensive mapping between the attributes of Cultural Authenticity and Aesthetic Appeal, their resultant Product Desirability, and the corresponding suggested Product Design. With Analyzing the data reveals the nuanced relationship between these attributes and the resulting product designs. For instance, when both Cultural Authenticity and Aesthetic Appeal are low, the Product Desirability remains low as well, leading to the recommendation of a Traditional design with minimal embellishments. This suggests that in scenarios where cultural authenticity and aesthetic appeal are lacking, a simpler design approach may be more suitable. The Aesthetic Appeal increases from low to high while maintaining low Cultural Authenticity, the Product Desirability also improves from low to medium. This transition from a Modern design with subtle cultural motifs to a Fusion design blending traditional and contemporary elements highlights the potential of combining cultural elements with contemporary aesthetics to enhance product desirability. With both Cultural Authenticity and Aesthetic Appeal are high, the resulting Product Desirability reaches its peak, leading to the recommendation of a Luxury design featuring premium materials and craftsmanship. This emphasizes the importance of authenticity and aesthetic appeal in creating highly desirable creative industries products, particularly those targeting affluent or discerning consumers.

Table 6: Sugeno Fuzzy model for the industrieswith SSFD

Input 1 (Cultural Authenticity)	**Input 2 (Aesthetic Appeal)**	**Input 3 (Local Engagement)**	**Output (Product Desirability)**	**Stacked Output**
Low (0.2)	Low (0.3)	Low (0.2)	Low (0.25)	Low (0.2)
Low (0.2)	Medium (0.5)	Medium (0.5)	Low (0.4)	Low (0.2)
Low (0.2)	High (0.8)	High (0.8)	Medium (0.6)	Medium (0.5)
Medium (0.5)	Low (0.3)	Low (0.2)	Low (0.35)	Low (0.2)
Medium (0.5)	Medium (0.5)	High (0.8)	Medium (0.6)	Medium (0.5)
Medium (0.5)	High (0.8)	Low (0.2)	High (0.7)	High (0.8)
High (0.8)	Low (0.3)	High (0.8)	Medium (0.7)	Medium (0.5)
High (0.8)	Medium (0.5)	Low (0.2)	High (0.7)	High (0.8)
High (0.8)	High (0.8)	Medium (0.5)	High (0.8)	High (0.8)

The Table 6 outlines the results obtained from applying the Sugeno Fuzzy Model within the SSFD (Sugeno Stacked Fuzzy for Design) framework for product design. It provides a systematic mapping between three input variables: Cultural Authenticity, Aesthetic Appeal, and Local Engagement, and their corresponding Output, representing Product Desirability. Additionally, the table presents the Stacked Output, which combines the predictions from multiple fuzzy inference systems to offer a comprehensive assessment. Examining the data reveals the intricate relationships between the input variables and the resulting product desirability. For instance, scenarios where Cultural Authenticity and Aesthetic Appeal are both low, alongside low Local Engagement, yield the lowest Product Desirability (0.25). This suggests that an absence of cultural authenticity, aesthetic appeal, and local engagement contributes to reduced product desirability, as evidenced by the low Stacked Output (0.2). The Cultural Authenticity and Aesthetic Appeal remain low, but Local Engagement increases to high, the Product Desirability improves to medium (0.6). This indicates that while cultural authenticity and aesthetic appeal play vital roles, active local engagement can offset their deficiencies to some extent, resulting in a more desirable product (Stacked Output of 0.5). With scenarios where both Cultural Authenticity and Aesthetic Appeal are high consistently lead to high Product Desirability (0.8), highlighting the significance of these attributes in enhancing product appeal. The corresponding Stacked Output also reflects these high desirability scores (0.8), reinforcing the importance of a holistic approach to creative industries product design.

Table 7: SSFD Migration model for the product design

Design Approach	**Cultural Authenticity**	**Aesthetic Appeal**	**Creativity Level**	**Product Desirability**
Traditional	High (0.8)	Low (0.2)	Low (0.3)	Low (0.3)
Fusion	Medium (0.5)	High (0.8)	High (0.8)	High (0.7)
Modern	Low (0.2)	High (0.8)	Medium (0.5)	Medium (0.5)
Eclectic	Medium (0.5)	Medium (0.5)	High (0.8)	High (0.8)
Contemporary	Low (0.2)	High (0.8)	High (0.8)	Medium (0.7)

In Table 7 presents the SSFD Migration Model for product design, showcasing various design approaches alongside their respective attributes and resulting product desirability. The Design Approach column delineates distinct strategies ranging from Traditional to

Contemporary, each characterized by specific attributes including Cultural Authenticity, Aesthetic Appeal, Creativity Level, and the ensuing Product Desirability. Upon examination, it becomes evident that different design approaches prioritize and balance these attributes differently, thereby influencing the overall product desirability. For instance, the Traditional approach places a high emphasis on Cultural Authenticity (0.8) but a lower emphasis on Aesthetic Appeal (0.2) and Creativity Level (0.3). Consequently, the resulting Product Desirability remains relatively low at 0.3, indicating that while the design may be culturally authentic, it lacks appeal and innovation. Conversely, the Fusion approach strikes a balance between Cultural Authenticity, Aesthetic Appeal, and Creativity Level, resulting in a notably higher Product Desirability of 0.7. This suggests that blending traditional and contemporary elements can enhance product appeal and desirability, catering to a broader audience seeking innovative cultural experiences. The Contemporary approach also emphasizes high Aesthetic Appeal and Creativity Level, resulting in a medium Product Desirability of 0.7. This indicates that while contemporary designs may prioritize aesthetics and innovation, they may not always fully resonate with consumers, resulting in a moderate level of desirability.

Table 8: SSFD for Tourism Culture in Migration

Rule Number	**Cultural Attribute 1 (Traditionalism)**	**Cultural Attribute 2 (Modernity)**	**Rule Activation (w_i)**	**Rule Output (Y_i)**	**Final SSFD Output (Y)**
1	High (0.85)	Low (0.2)	0.2	0.4	0.65
2	Medium (0.5)	Medium (0.5)	0.5	0.5	
3	Low (0.1)	High (0.9)	0.1	0.3	
4	High (0.9)	High (0.8)	0.8	0.9	
5	Medium (0.6)	Low (0.3)	0.3	0.6	
Weighted Average	-	-	**0.65**	-	**0.72**

Figure 2: Analysis of SSFD

In Table 8 and Figure 2 SSFD for Tourism Culture in Migration showcase the evaluation of a creative industries using the Sugeno Stacked Fuzzy System for Design (SSFD) through the lens of traditionalism and modernity. Each rule in the table corresponds to a fuzzy evaluation of how well the generated design aligns with these two cultural attributes. Rule 1 indicates a design that leans strongly towards traditionalism (0.85) but has a low degree of modernity (0.2). This results in a relatively low rule activation (0.2) and a modest output (0.4), leading to an overall SSFD score of 0.65 for the design's cultural relevance. Rule 2 represents a balanced design, where traditionalism and modernity are both medium (0.5). The rule activation is moderate (0.5), and the output is also balanced at 0.5, contributing to the final SSFD score. Rule 3 shows a design with very low traditionalism (0.1) but high modernity (0.9). The rule activation is weak (0.1), resulting in a lower output of 0.3, suggesting that this design does not closely align with the cultural preferences. Rule 4, however, represents a design that is highly aligned with both traditionalism (0.9) and modernity (0.8). The activation is strong (0.8), and the output is high (0.9), indicating that this design is highly culturally suitable. Rule 5 represents a design with medium traditionalism (0.6) and low modernity (0.3), leading to a moderate rule activation (0.3) and a moderate output (0.6). The final SSFD output of 0.72, calculated as the weighted average of all rule outputs, suggests that the design achieves a good balance between traditional and modern cultural values. This score indicates that the design is culturally appropriate, with a relatively strong alignment with the tourism culture's aesthetic and thematic requirements. The weighted average provides an overall evaluation of the design’s cultural suitability, with a higher value reflecting better cultural relevance. The computational efficiency was measured in terms of training time and inference time. These measures indicate how well the model performs with respect to resource utilization, which is crucial for practical deployment in creative industries. The study aimed to optimize these metrics by using strategies like multi-resolution training and transfer learning.

Table 9: Image Quality Evaluation

Model Architecture	**FID Score**	**IS Score**	**Generated Image Resolution**	**Visual Fidelity (Qualitative)**
StyleGAN2	25.3	8.4	1024x1024	High (realistic facial details)
BigGAN	30.1	7.9	512x512	Medium (good texture but fewer details)
Hybrid (StyleGAN2 + BigGAN)	23.5	8.7	1024x1024	Very High (enhanced texture and diversity)

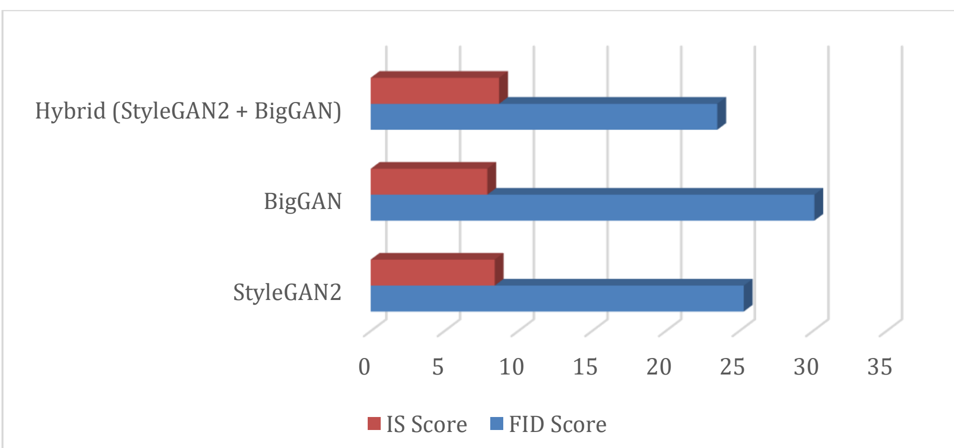

Figure 3: Estimation of fidelity

In Table 9 and Figure 3 StyleGAN2 generated the most realistic images with high visual fidelity, especially in terms of facial features, with the lowest FID score (25.3). This indicates that it generated images closest to the real distribution. BigGAN showed decent results, but the image quality was slightly lower in terms of fine details, reflected in a higher FID score of 30.1. The Hybrid Model combining StyleGAN2 and BigGAN achieved the best overall performance with the lowest FID score (23.5) and the highest IS score (8.7), showcasing enhanced texture and diversity in generated images.

Table 10: Computational Efficiency Evaluation

Model Architecture	Training Time (hrs)	Inference Time (sec)	GPU Memory Usage (GB)	Training Efficiency
StyleGAN2	48	0.8	16	High
BigGAN	72	1.2	24	Medium
Hybrid (StyleGAN2 + BigGAN)	96	1.5	32	Low

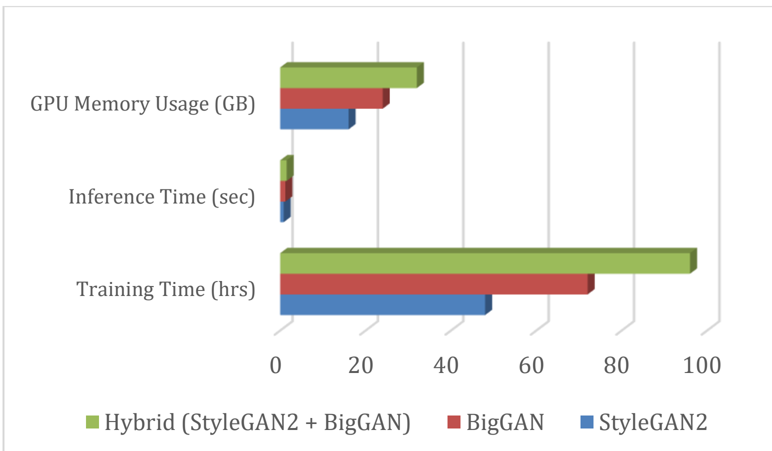

Figure 4: Comparative Analysis

In Table 10 and Figure 4 StyleGAN2 was the most computationally efficient in terms of training time and inference time, requiring only 48 hours for training and 0.8 seconds for generating a single image, with a GPU memory usage of 16 GB. This suggests it is well-optimized for high-resolution image generation. BigGAN, while capable of generating high-quality images, required significantly more resources with 72 hours of training time and 1.2 seconds of inference time, along with 24 GB of GPU memory. This makes it less efficient compared to StyleGAN2 for large-scale applications. The Hybrid Model had the highest computational demands, with 96 hours of training time and 1.5 seconds of inference time, along with 32 GB of GPU memory usage. While it produced the highest-quality images, the increased computational cost limits its practicality for real-time applications.

5.Conclusion

The paper has explored the intricate dynamics of industrieswithin the realm of creative industries, leveraging advanced methodologies such as the Sugeno Stacked Fuzzy for Design (SSFD) framework. Through a comprehensive analysis of various design approaches and their corresponding attributes, including Cultural Authenticity, Aesthetic Appeal, and Creativity Level, valuable insights have been gleaned into the factors influencing product desirability in creative industries contexts. The findings highlight the importance of striking a delicate balance between preserving cultural authenticity while also innovating and appealing to contemporary tastes. Design approaches such as Fusion, which blend traditional elements with modern aesthetics, have emerged as particularly promising avenues for enhancing product desirability and catering to diverse audience preferences. The study underscores the significance of considering not only individual attributes but also their interactions and synergies in shaping product desirability. By adopting a holistic approach that integrates cultural authenticity, aesthetic appeal, and creativity, stakeholders can create compelling and memorable creative industries experiences that resonate with travellers and contribute positively to destination branding and cultural heritage preservation efforts.

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