Salud, Ciencia y Tecnología - Serie de Conferencias. 2025; 4:1387
doi: 10.56294/sctconf20251387

ORIGINAL

The application of digital people in cultural and creative products in the context of artificial intelligence

La aplicación de las personas digitales en productos culturales y creativos en el contexto de la inteligencia artificial

Yue Zhuo[1], Hongli Pang[1]

[1]Department of economic Management, Shanxi TongWen Vocational and Technical College. Jinzhong 032000, Shanxi, China.

Cite as: Zhuo Y, Pang H. The application of digital people in cultural and creative products in the context of artificial intelligence. Salud, Ciencia y Tecnología - Serie de Conferencias. 2025; 4:1387. https://doi.org/10.56294/sctconf20251387

Submitted: 29-06-2024 **Revised:** 17-11-2024 **Accepted:** 25-02-2025 **Published:** 26-02-2025

Editor: Prof. Dr. William Castillo-González

Corresponding Author: Yue Zhuo

ABSTRACT

Introduction: one of the most significant advancements in the contemporary creative sector is the integration of digital technologies and artificial intelligence (AI) in the design and development of cultural and creative products (CCP). It investigates the use of AI-driven digital technologies, focusing on their role in enhancing aesthetics, streamlining design processes, and improving user experiences in CCP.
Method: the applies advanced AI methods, including the Penguin Search Optimization Malleable Decision Tree (PSO-MDT), and shape grammar techniques. Shape grammar is utilized to derive design guidelines for artistic and cultural objects, while MDT predicts the most suitable design elements for cultural products. The Intelligent Product System (IPS) is employed to optimize the design process for CCP.
Results: the demonstrates that optimized designs achieved through these AI methods exhibit scaling values approaching near-maximum levels, signifying improved aesthetic and functional outcomes. This validates the effectiveness of AI in enhancing cultural product designs.
Conclusions: the transformative potential of AI-driven digital technologies in fostering innovation within the creative sector. By emphasizing the application of advanced AI methodologies, it offers valuable insights into improving the aesthetic and practical attributes of CCP and guiding future developments in this field.

Keywords: Digital People; Cultural and Creative Products (CCP) Design; Penguin Search Malleable Decision Tree (PSO-MDT); Shape Grammar.

RESUMEN

Introducción: uno de los avances más significativos en el sector de la creación contemporánea es la integración de las tecnologías digitales y la inteligencia artificial (IA) en el diseño y desarrollo de productos culturales y creativos (CCP). Investiga el uso de tecnologías digitales de inteligencia asistida, centrándose en su papel en la mejora de la estética, la racionalización de los procesos de diseño y la mejora de las experiencias de usuario en CCP.
Método: aplica métodos avanzados de IA, incluyendo el Penguin Search Optimization Malleable Decision Tree (PSO-MDT), y técnicas de gramática de formas. La gramática de la forma se utiliza para derivar directrices de diseño para objetos artísticos y culturales, mientras que MDT predice los elementos de diseño más adecuados para los productos culturales. El sistema de producto inteligente (IPS) se emplea para optimizar el proceso de diseño para CCP.
Resultados: el demuestra que los diseños optimizados logrados a través de estos métodos de IA muestran valores de escala que se acercan a niveles casi máximos, lo que significa mejores resultados estéticos y funcionales. Esto valida la eficacia de la IA en real diseños culturales del producto.

Conclusiones: el potencial transformador de las tecnologías digitales impulsadas por AI en el fomento de la innovación dentro del sector creativo. Al enfatizar la aplicación de metodologías avanzadas de IA, ofrece valiosas perspectivas para mejorar los atributos estéticos y prácticos de los CCP y guiar los desarrollos futuros en este campo.

Palabras clave: Digital People; Cultural and Creative Products (CCP) Design; Penguin Search Malleable Decision Tree (PSO-MDT); Shape Grammar.

INTRODUCTION

There has been a dramatic change in historic sites and institutions in the past century. While earlier they emphasized the preservation of places, things, and evidence, activities revolved around the communication of knowledge.[1] During the later part of the 20th century, museums were inclined to the user; therefore, individuals were able to critically think about the places and objects, draw their inferences, and engage with the things.[2] The text emphasizes that significant developments in AI need not necessitate sophisticated AI, which does not need to be distinguishable from human behavior or capable of emulating human reasoning. Instead, AI can accomplish simple jobs that humans have historically performed, such as picture recognition and natural language processing (NLP), without requiring an ideal human counterpart. Creativity is defined as the ability to generate unique and adaptable ideas that could be used to solve problems and develop methods, processes, and products. Individual creativity is critical to business innovation and success.[3] Globalization and the opportunity for the worldwide promotion of goods and services have increased the influence of creativity and artistic industries on the global economy. Cultural heritage presents both opportunities and problems for building effective Information and Communication Technology (ICT) solutions that provide democratic access to all.[4]

Digitalization alone is insufficient; material must also be made accessible to people with various disabilities. Efficient information presentation approaches should be brought into the design of the online environment that attracts visitors. ICT is a legitimate choice for building remote visiting experiences; however, elite views on accessibility and knowledge technology are leading to barriers to access and inclusion, like lockdowns due to pandemics, but only limited benefits to minorities, including the blind. The rapid advances of artificial intelligence (AI) as well as electronic devices have ensured that many businesses, including the cultural and artistic fields, are being transformed.[5] Advances in technology are increasingly applied to alter how cultural products are created, produced, and consumed. With a growing demand for unique, creative, and cultural products, there is an immediate need to develop technologies that enhance the aesthetic as well as functional properties of the products while hastening the design process.[6] Among the many interesting advancements in this field, digital people stand out as synthetic human-like entities or AI tools. These digital humans can be utilized for a great diversity of tasks, such as providing designers with a basis for ideas, generating interactive experiences, or even the creative expression of cultural stories. Through the integration of AI with aesthetic principles, it is possible to create products that resonate with cultural heritage but equally include new and contemporary elements.[7] This work aims to develop further culturally and creatively advanced product designs through the introduction of PSO-MDT. The best features related to the best possible patterns, colors, or shapes as predicted, will be used for designing the products that are aesthetically pleasing and culturally important, thus engrossing and appealing to the people better.

The use of electronic devices to offer inclusive museum and culturally relevant experiences was examined in the article.[8] It emphasized the importance of individualized delivery across many competence areas, including interaction and pedagogical design. The report developed an analytical structure for online experiences and proposed future research directions to improve cultural heritage content accessibility. With a focus on perceived privacy and confidence issues, author[9] explored the relationship between AI risks in electronic health care and accountable AI. It looked into the diminishing influence of different dangers using the perceived risk theory. The dynamism and autonomy of virtual reality (VR) training in numerical media art design were highlighted in the reference.[10] It emphasized the technical advantages of artificial intelligence technologies as well as enhancing student learning. Experimental results indicate that this technology, which combines AI algorithms, has possible value and practical relevance in multimedia art creation. Education was critical for people to gain necessary skills, and the framework aimed to foster a culture of competence. Virtual reality and intelligent systems for teaching have all contributed to personalized education. With an emphasis on creativity, thinking critically, solving problems, and logical thinking, author[11] aimed to demonstrate how technological advancements like AI affect human behavior development and skill learning.

Work[12] examined how AI affects creativity in the highly automated marketing sector. The research, which covers 156 studies between 1990 and 2021, offered a fresh paradigm for examining innovation in AI and advertising. It also included a typology of essential marketing talents and the effects of AI abilities on these activities, giving readers a thorough knowledge of AI integration in marketing. In examining the connection between AI and marketing philosophy, author(13) suggested how AI systems might improve strategic choices made by entrepreneurs. Research provided real-world examples and actionable inferences for new organization approaches and performances. A paradigm for comprehending design and creativity in the era of AI was presented in the work.(14)

They think about the implications for creative philosophy and design. In particular, to find that human design progressively developed a sense-making action, that is, identifying the difficulties that should be solved as computers replace creative problem-solving. According to the concept,(15) young children can explore AI in a way that is suitable for their culture, and AI knowledge was a crucial part of numerical competency. One excellent curriculum, "AI for Kids," demonstrated how teachers can offer traditionally sensitive analysis opportunities for kids to cooperate. A knowledge-based approach and transaction cost theory were used in the reference(16) to examine how Not-Invented-Here Syndrome (NIHS) affects innovation efficiency and a technology approach. It found that high Environmental Aspect Impact Analysis (EAIA) amplified the negative consequences of NIHS, suggesting that NIHS is a feature of the digital age rather than a pre-digital phenomenon. AI-driven campaign transformation, lead generation, and customer management were all being impacted by digital marketing.(17) However, ethical issues and real-world applications were despite their infancy. To fully grasp AI's potential impact, more investigation was mandatory to regulate its full possible and restrictions in the advertising industry.

The integration of digital people in cultural and creative products, driven by artificial intelligence, raises concerns about authenticity, ethics, and the preservation of cultural identity. These technologies challenge traditional creative processes and demand new frameworks for ownership, representation, and collaboration. The problem lies in balancing innovation with respect for cultural values and human creativity. To develop further culturally and creatively advanced product designs through the introduction of PSO-MDT. The best features related to the best possible patterns, colors, or shapes as predicted, will be used for designing the products that are aesthetically pleasing and culturally important, thus engrossing and appealing to the people better.

Key Contribution:

- Explores AI-driven technologies enhancing aesthetics, design processes, and user experiences in cultural and CCP.
- Utilizes advanced AI methods, including PSO-MDT, and shape grammar, for optimizing CCP design.
- The use of IPS to enhance CCP design processes and improve aesthetic outcomes.

This paper falls into five distinct phases: Phase 1 introduces the background study and objectives of the research; Phase 2 explains the methods, Phase 3 is the presentation of the results and discussion, and Phase 4 concludes the study with key findings and future research directions.

METHOD

Study investigates integrating Shape Grammar and Penguin Search Optimization-based Malleable Decision Trees (PSO-MDT) to optimize the design of CCP, preserving their cultural essence while fostering innovation. Below is a refined outline of the research approach.

Deriving strategy elements for cultural and creative products (CCP) using shape grammar

The design patterns minimalistic (Grid), modern (Meshes), and traditional (Cluster) are used as data inputs to forecast and optimize designs with shape grammar. These patterns govern AI-driven processes because they produce as well as refine artistic and intellectual designs for items depending on consumer preferences. Shape grammar, as initially developed for painting and sculpture, has expanded to become a powerful tool employed by architectural design, product development, visual design, and industrial design. Principles are defined for the alteration of shape elements that results in new design features having features that are derived from the original forms. This methodological approach maintains cultural aspects with the growth of efficiency in the design process by automating complex activities, reducing time and labor requirements, and encouraging creativity. Shape Grammar Induction Rules can be represented as a quaternion in equation (1):

$$SG = (T, K, Q, J) \quad (1)$$

The text explains a system in which S is a limited number of forms, K is a significant collection of labels, and preexisting shapes and labels can be combined to create labeled curves. The collection of assigned curve is indicated as $(T,K)^+$ whereas the originally assigned curve formed by shaped implication is designated as→β. The system comprises a limited number of inference rules, where α is a left-assigned curve, β is a right-assigned curve, and the value J is the labeled starting shape. Figure 1 shows the semantic framework of shape grammar, which generates new figures based on original shapes using different instructions.

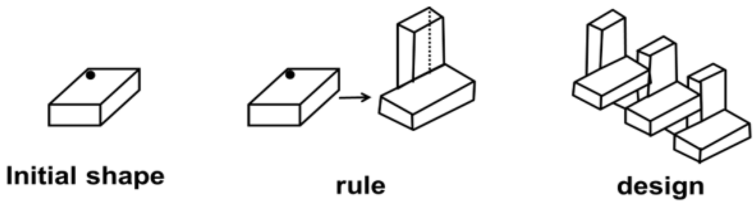


Figure 1. Semantic framework of shape grammar

Figure 2 depicts the parametric shape grammar derivation approach, which uses organize points to express all form elements. This streamlines the method and increases computing efficiency. The generated shapes are allocated to certain threshold spaces, which offer calculated limits for spatial positioning and shape differences, improving both the correctness and flexibility of CCP design.

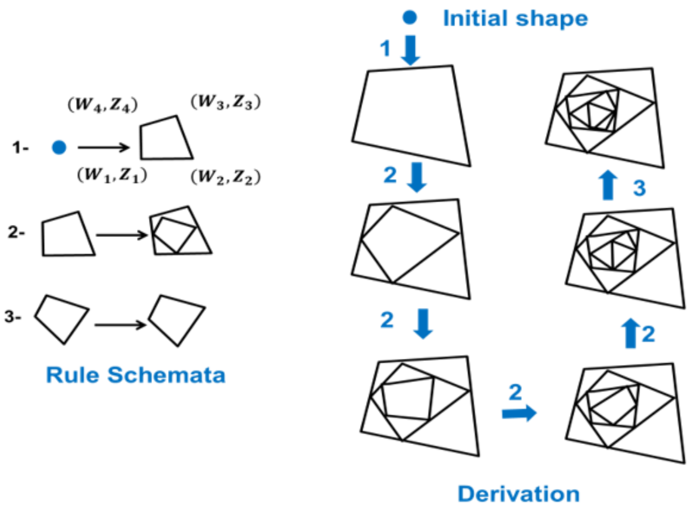


Figure 2. Parametric shape grammar derivation approach

Shape Grammar Reasoning Rules: there are two types of inference rules in CCP design. They are generative and modification rules. Generative rules add or replace a shape element, while modification rules change or modify the shapes already existing elements. The above criteria allow the development of an existing design structure. The desirable aesthetics remain there, but the novelty introduced makes a difference. In the technique, the leverage B-splines and reflection as modification criteria to alter shape elements, resulting in smooth curve transformations and balanced design features. These criteria help to fine-tune CCP designs, retaining brand essence while encouraging innovation.

B-splines

Cardinal B-splines, presented here in their Fourier transform form in equation (2).

$$\hat{\beta}^m(\omega) = \left(\frac{1-f^{-j\omega}}{j\omega}\right)^{m+1}, m \in N, \qquad (2)$$

Fractional splines are useful in computational design, particularly in CCP development. Traditional splines have limitations due to their fixed order of smoothness and approximation. Fractional B-splines with a fractional exponent α∈Rallow continuous adjustment of smoothness and precision. The distinct two types of fractional B-splines: The fundamental one, β_+^α and the symmetric one, β_*^α are given in equations (3 and 4).

$$\hat{\beta}_+^\alpha(\omega) = \left(\frac{1-f^{-j\omega}}{j\omega}\right)^{\alpha+1} \qquad (3)$$

$$\hat{\beta}_*^\alpha(\omega) = \left(\frac{1-f^{-j\omega}}{j\omega}\right)^{\frac{\alpha+1}{2}} \left(\frac{1-f^{j\omega}}{-j\omega}\right)^{\frac{\alpha+1}{2}} \qquad (4)$$

Mutually 2 categories are in $K^1(R)$ifα>-1 and in $K^2(R)$ifα>-1/2. Additionally, they presented an additional factor τ∊Rlabeling modifications in the time area, as shown in equation (5).

https://doi.org/10.56294/sctconf20251387

$$\hat{\beta}^{\alpha}_{\tau}(\omega) = \left(\frac{1-f^{-j\omega}}{j\omega}\right)^{\frac{\alpha+1}{2}-\tau}\left(\frac{1-f^{j\omega}}{-j\omega}\right)^{\frac{\alpha+1}{2}+\tau} \quad (5)$$

All of the B-splines serve scaling reasons and can be utilized to necessitate dyadic multi-resolution evaluations of $K^2(R)$. However, they are the only actual value. Modern splines are defined as extending a creation one step further by using complex-valued coefficients in their place of the actual ones. These splines, particularly the causal splines, are applied to model complex transitions between cultural elements and modern design requirements, therefore flexibility and seamless integration of varying design complexities.

Cultural and Creative Product Element Extraction

The process of extracting CCP elements involves analyzing graphic elements from complex designs. Three primary shape patterns are polygons, meshes or grids, and clusters. These shapes are outlined and converted into polygons, grids, or clusters. Polygons represent closed, multi-sided shapes, grids form structured layouts of repeating patterns, and clusters represent grouped elements that could vary in size and shape but are unified in design. These patterns serve as the foundation for applying shape grammar rules, enabling the extraction of key design elements that adhere to cultural aesthetics. The final output is a set of shapes that can be modified or combined, preserving the creative intent and cultural identity of the invention are indicated in figure 3.

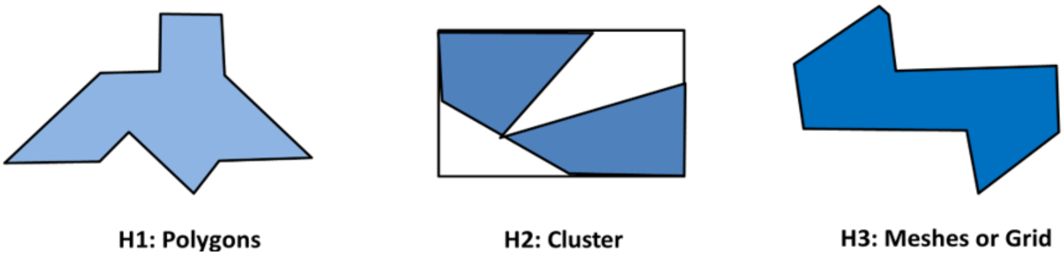
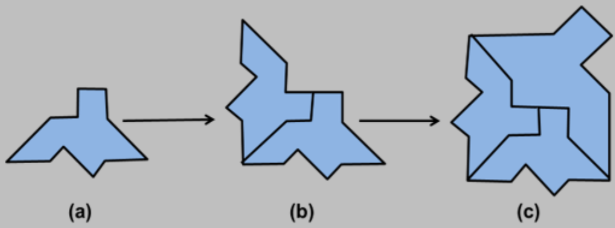
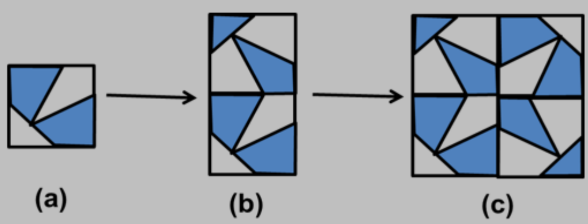
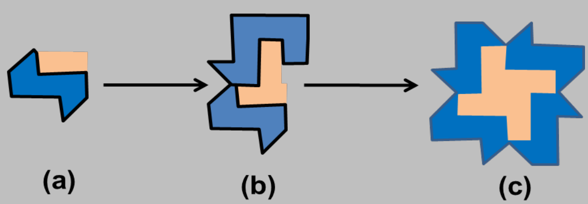


Figure 3. Fundamental of elements Patterns based on the H1-Polygons, H2-Cluster, H3-Meshes and grid

Redesigning and extending fundamentals of cultural and creative products

Table 1. Analyzing the Fundamentals of creative products designs model

Numbering	Pattern	Name of the pattern
H1		Polygons
H2		Cluster
H3		Meshes or grid

The method employs three fundamental shape patterns: polygons, clusters, and meshes (grids). These patterns follow basic form grammar rules and are named Rule 1- Rule 7. These rules are: Rule 1 Repeat, Rule 2 Mirror, Rule 3 Add and Delete, Rule 4 Zoom, Rule 5 Rotate, Rule 6 Mirror, Rule 7 Downward Shift, and Rule 8

https://doi.org/10.56294/sctconf20251387

Bessel Curve. These patterns' basic aspects are form, color, and composition, with each type providing unique features. Polygonal designs stress angularity and precision, whereas cluster patterns foster coherence and unity. Mesh/grid designs are organized and regular, which promotes uniformity and balance. The design process involves analyzing specific pattern elements utilizing form grammar rules and it is presented in table 1.

H1 is created from a polygon pattern utilizing mirroring and repeating rules, resulting in symmetrical and tessellated objects that form a more coherent design.

H2 is created by rotating and repeating a cluster pattern, resulting in a changing, interconnecting structure.

H3 is created by rotating and repeating a mesh/grid pattern, resulting in an organized and ordered layout that is both visually pleasing and useful.

Enhancing cultural and creative design using the Penguin Search malleable decision tree (PSO-MDT)

The PSO-MDT model allows a Malleable Decision Tree to be incorporated into Penguin Search Optimization that can effectively optimize cultural and artistic product design. PSO finds the optimal attributes of design like color, shape, or pattern and MDT then predicts the best combination as per the design attributes. Together, refine designs by balancing creativity, functionality, and cultural relevance.

Malleable decision tree (MDT)

A particularly very effective methodology to use when exploring a design space is the model of decision tree. In the given model, an MDT can predict which design factor such as color, pattern, or shape would be optimal for that particular product. As with the MDT approach, each leaf node represents a different expression of a design, made up of attributes and their possible values. At every inner node in the tree that is not a leaf node, the MDT procedure takes one of the attributes, splits into the branches corresponding to its values, and considers, at the current node in the subset of conceptual examples, its possible values of this attribute. This step is repeated sequentially to the non-leaf nodes for enhancing the decision-making process. An algorithm to create a decision tree includes specifying the following:

1. A rule for determining which characteristic to split samples at a node.
2. A rule for selecting a specific split of samples.
3. A rule to stop dividing a node, resulting in it becoming a leaf node.
4. A leaf-to-class allocation technique.

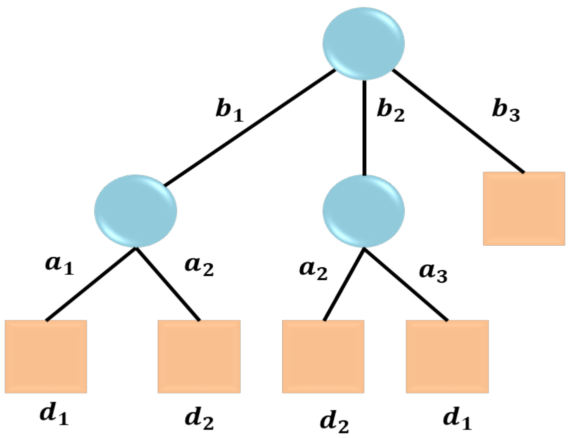


Figure 4. Structure of Malleable decision tree

In the figure 4, it focuses on how Malleable Decision Trees (MDT) helps predict the best design elements such as colors, shapes, and patterns for a product. Let $B=\{B_1,B_2,\ldots,B_n\}$ be a set of design attributes (e.g., color, shape, pattern), and let $D=\{D_1,D_2,\ldots,D_o\}$ be a set of design classes (e.g., modern, classic). Each example in the dataset is represented as a tuple $\langle U_1, U_2,\ldots, U_n, D_l\rangle$, where $U_j \in Range(B_j)$, $j=1,\ldots,n$, and $D_l \in D$, is the corresponding design class. The MDT algorithm calculates the probability O_T, D_l of each class D_l occurring in a set T of examples, which is the proportion of examples in T that belong to class D_l. The uncertainty or randomness of the design class distribution in T is measured using an information measure. The algorithm then selects the attribute B_j that reduces this uncertainty B_j: $T_i=\{f \in T \mid B_j=U_i \text{ forf}\}$ the most, helping to predict which design elements (color, shape, or pattern) will work best for the product based on the patterns in the data are followed in equation (6).

$$J(T) = -\sum_{l=1}^{o} O_T, D_l log_2 O_T, D_l \qquad (6)$$

MDT partitions T into sets $T_{(i)}$ resulting in subsets with less random distribution of examples. The information

https://doi.org/10.56294/sctconf20251387

entropy of the resultant screen is determined by dividing T into sets T_i, where all examples in T have value B_j for feature B in equation (7).

$$F(B_j,T) = \sum_{U_i \in Range(B_j)} \frac{|T_i|}{|T|} J(T_i) \quad (7)$$

For additional separating of a node in the tree, MDTselects the characteristic which maximizes are in equation (8).

$$Gain(B_j,T) = J(T) - F(B_j,T) \quad (8)$$

The MDT allows for adaptive prediction, ensuring that the design elements chosen align with specific goals and preferences, creating the most effective design combination for the product.

Penguin Search Optimization (PSO)

Penguin search optimization is a new metaheuristic inspired by the collaborative and efficient strategies applied by penguins in searching for food. This approach mirrors how the penguins manage to harmonize efforts directed toward a common goal to get optimal results; thus, a designer may select the best patterns, colors, and shapes for a product. The algorithm assesses several design aspects in terms of their "energy efficiency," sort of weighing the potential utility of a design vs. the resources used to produce it. Similarly, penguins weigh the potential value of a foraging site against available resources and work put in; this method systematically explores design options and will favor the ones that yield the highest impact with the least expenditure of resources involved, thus ensuring an optimized final product. The following rules are outlined in Algorithm 1.

Algorithm 1 for PSO:

Rule 1: the penguin community is divided into several groups.

Rule 2: each group can accommodate a different number of penguins, depending on the local food available.

Rule 3: penguins search and wander arbitrarily to find food as long as oxygen is available.

Rule 4: it allows for multiple dives to a single depth. Penguins in a group seek from specific positions ("hole i") and depths ("$i_1, i_2, \ldots, i_m$").

Rule 6: penguins within a group forage randomly and communicate their discoveries with peers after multiple dives to promote intra-group communication.

Rule 7: the number of penguins at each level varies according to food availability.

Rule 8: insufficient food causes a group, or potentially the entire group, to leave to a different hole, allowing for inter-group communication.

Rule 9: the collection that consumes the most fish reveals the precise location of the abundant food source, marked by the gap and level.

The PSO algorithm makes use of design elements like color, shape, or pattern as penguins are placed at different levels and locations. The process begins with random starting points, reproducing the way penguins search for fish. Groups of penguin design elements communicate and share information about their solutions, with less successful groups following better strategies. Each group explores different design variations and refines their positions based on previous success. Using equation (9), an updated solution is calculated for each penguin in each group.

$$C_{new} = C_{lastlast} + rand * |W_{localBest} - W_{locallast}| \quad (9)$$

Rand() generates a random number for the range. There are three options available: the best-localized solution, the most updated solution, and the novel approach. The modified solution (equation 9) is calculated for each penguin in each group. After multiple dives, penguins communicate the most effective solution by consuming the most fish. Finally, the possibility of a new pattern of holes and levels is estimated. The algorithm determines the best design solution through iterative evaluations, updating probabilities upon successful outcomes. The algorithm formulates a more refined solution for each group to maximize impact and effectiveness. The hybrid method integrates Penguin Search Optimization (PSO) with Malleable Decision Trees (MDT) to optimize CCP. PSO refines design elements such as patterns, colors, and shapes through adaptive exploration, whereas MDT predicts optimal combinations by reducing uncertainty. Together, they enhance creativity, functionality, and cultural relevance in design processes.

RESULTS

Python 3.10 or 3.11 is recommended for developing CCP with AI-driven optimization. The Python ecosystem allows machine learning, data manipulation, and design optimization support through libraries such as TensorFlow, PyTorch, sci-kit-learn, and NumPy. A research paper compares three design patterns: Minimalistic (Grid), Modern (Meshes), and Traditional (Cluster) using AI-driven approaches. Minimalistic designs allow customization and aesthetic variety, and modern designs achieve high user satisfaction, visual harmony, and sustainability. The traditional designs balance innovation and sustainability, offering cultural resonance and adaptability. Models such as PSO-MDT demonstrate their effectiveness in achieving aesthetic and functional optimization.

These will clearly analyze their advantage within minimalistic, traditional, and modern design patterns from analysis involving design flexibility, user satisfaction, and market demand: Modern leads, holding the maximum user satisfaction as 91 % as well as a high degree of market demand at 85 % plus a maximum flexibility score (9). Traditional designs also perform well, scoring 87 % in user satisfaction, 9 in the flexibility score, and a high market demand of 79 %, which shows they can achieve cultural relevance without sacrificing functional flexibility. Minimalistic designs score a bit lower, with user satisfaction at 85 % and flexibility score at 8, and have a more modest market demand of 70 %, which reflects their niche appeal in simpler, more streamlined applications. These result in modern designs being the most versatile and in-demand, traditional patterns hold much value in their balance of flexibility and user-centric features, and minimalistic patterns cater to a specific audience that prefers simplicity and elegance, as displayed in table 2 and figure 5.

Table 2. Design Flexibility vs. User Satisfaction

Design Pattern	User Satisfaction (%)	Flexibility Score (1-10)	Market Demand (%)
Minimalistic	85	8	70
Traditional	87	9	79
Modern	91	9	85

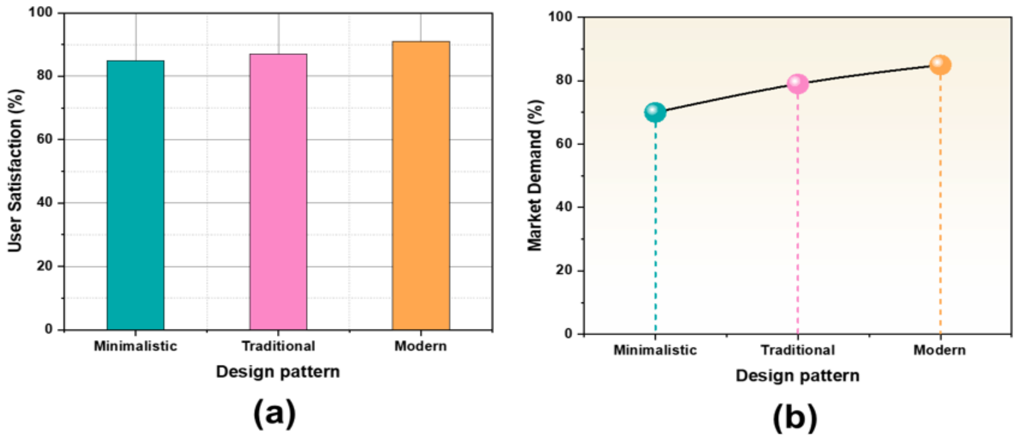


Figure 5. Evaluation of (a) User Satisfaction and (b) Market Demand for Design Patterns

Table 3 depicts the user feedback on design elements across minimalistic, traditional, and modern patterns, revealing distinct strengths for each style. Pattern 1 (Minimalistic) excels in customization ease (4,9) and aesthetic variety (4,8), reflecting its adaptability and diverse appeal, though it scores slightly lower in sustainability (4,0). Pattern 2 (Classic) is remarkable for innovation (4,6) and sustainability (4,2), which allows the pattern to combine tradition with ecologically friendly design without compromising on performance in material quality (4,1) and aesthetic variety (4,3).

Table 3. Performance of Design Elements Based on User Feedback

	Rating (1-5)		
Design Element	Pattern 1 (Minimalistic)	Pattern 2 (Traditional)	Pattern 3 (Modern)
Visual Harmony	4,2	4,0	4,8
Innovation	4,5	4,6	4,7
Material Quality	4,2	4,1	4,5
Customization Ease	4,9	4,7	4,1
Sustainability	4,0	4,2	4,9
Aesthetic Variety	4,8	4,3	4,6

Pattern 3 (Contemporary) boasts the highest ratings on average, with the highest marks on visual harmony (4,8), sustainability (4,9), and material quality (4,5), which reflects that the pattern is the best to achieve a balance between style, quality, and ecological awareness. All patterns score above 4,5 in innovation, reflecting their effectiveness in meeting user expectations for creativity. Such findings highlight the strengths of modern patterns in overall quality while emphasizing the unique advantages of minimalistic designs in customization and traditional designs in cultural resonance, providing actionable insights for future design strategies.

In table 4 and figure 6, the performance of three algorithms, Penguin Search Optimization (PSO), Decision Tree (DT), and the Penguin Search Optimization-based Malleable Decision Tree (PSO-MDT), is evaluated for optimizing CCP designs in terms of solution quality, convergence time, and design diversity. DT has achieved a solution quality of 88 %, with a convergence time of 10,2 seconds and a diversity score of 7, showing balanced performance. PSO performs worse in terms of solution quality (85 %) and diversity (6) but converges faster at 9,8 seconds, whereas PSO-MDT does better than both: with a solution quality of 92 %, a diversity score of 9, and a convergence time of 10,5 seconds, it shows that PSO-MDT is stronger to create innovative, high-quality designs within a reasonable period. It underscores the potential of PSO-MDT as the most effective approach for enhancing the aesthetic and functional aspects of cultural products while fostering greater innovation and personalization.

Table 4. Performance Evaluation of PSO, DT, and PSO-MDT Algorithms for Optimizing CCP Designs

Algorithm	Solution quality (%)	Convergence time (s)	Diversity score(1-10)
DT	88	10,2	7
PSO	85	9,8	6
PSO-MDT	92	10,5	9

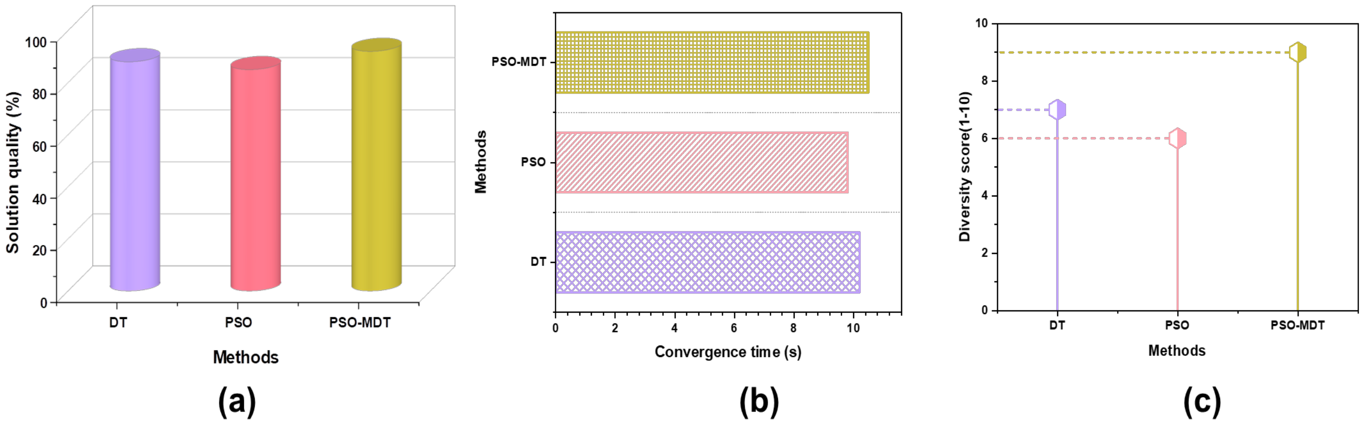


Figure 6. Performance Comparison of Algorithms (PSO, DT, and PSO-MDT) in Solution Quality (a), Convergence Time (b), and Diversity Score (c)

It focuses on how AI-driven methods like PSO-MDT can effectively optimize CCP designs, with modern patterns excelling in versatility, user satisfaction, and market demand. However, its limitations include the narrower appeal of minimalistic designs and potential challenges in balancing traditional patterns' cultural resonance with innovation that needs further refinement to address diverse user preferences comprehensively.

DISCUSSION

The integration of digital people into cultural and creative products, enabled by artificial intelligence, revolutionizes storytelling, marketing, and user experiences, blending human-like virtual personas with advanced technology to enhance creativity, engagement, and cultural innovation across diverse industries. PSO and DT methods, while valuable, exhibit notable limitations when applied to digital people in cultural and creative products in artificial intelligence. PSO is inspired by the foraging behavior of penguins but can struggle with complex, high-dimensional datasets often present in AI-driven creative domains. It risks premature convergence to local optima, limiting its effectiveness in exploring the nuanced and abstract spaces required for cultural product development. Furthermore, PSO's reliance on parameter tuning can lead to inefficiencies, particularly when applied to dynamic creative processes involving evolving user preferences. DT, on the other hand, are interpretable but often lack the capacity to capture intricate patterns and relationships. They tend to overfit the data, particularly in scenarios requiring adaptability, such as designing personalized digital avatars or culturally contextualized content. DTs may struggle with the non-linearities and high variance inherent in creative industries. Both methods are also limited in incorporating subjective, emotional, or aesthetic factors crucial for cultural products. This restricts their ability to deliver rich, meaningful experiences demanded by modern AI applications in the creative space. Enhancements or integration with advanced models like deep learning may be necessary to address these gaps. To overcome these limitations, integrating PSO-MDT combines PSO's optimization capabilities with a MDT structure, enabling adaptive learning, improved handling of complex patterns, and enhanced personalization for creative, cultural AI applications.

CONCLUSIONS

Finally, AI-based techniques, like the PSO algorithm with Malleable Decision Trees (PSO-MDT), significantly improve CCP design. Challenges on aesthetics, functionality, and user preference were effectively addressed using the PSO-MDT hybrid model that outperformed the standalone PSO and DT models at 92 % solution quality, a diversity score of 9, and convergence time of 10,5 seconds. These metrics illustrate its power to work efficiently with innovative, flexible, and culturally relevant designs. In this respect, the PSO component properly explores as many diverse design possibilities as creativity and uniqueness, but MDT refines it by evaluating and predicting optimally. It enhanced all three factors, namely visual harmony, sustainability, and user satisfaction in the CCP designs. This symbiosis represented a transformative moment in AI and the creative industry. The limitations include the narrower appeal of minimalistic designs and potential challenges in balancing traditional patterns' cultural resonance with innovation that needs further refinement to address diverse user preferences comprehensively. Future applications of such hybrid methodologies could revolutionize design processes by providing intelligent, data-driven tools for creating aesthetic yet functionally robust products, bridging cultural heritage with modern innovation.

BIBLIOGRAPHIC REFERENCES

1. Chapman JM, Schott S. Knowledge coevolution: generating new understanding through bridging and strengthening distinct knowledge systems and empowering local knowledge holders. Sustainability Science. 2020 May;15(3):931-43. https://doi.org/10.1007/s11625-020-00781-2

2. Davis JF. Interactive, Participatory Educational Spaces in Denver Art Museum's Martin Building (Doctoral dissertation). http://dx.doi.org/10.26153/tsw/14552

3. Żywiołek J, Tucmeanu ER, Tucmeanu AI, Isac N, Yousaf Z. Nexus of transformational leadership, employee adaptiveness, knowledge sharing, and employee creativity. Sustainability. 2022 Sep 15;14(18):11607. https://doi.org/10.3390/su141811607

4. Briciu A, Briciu VA, Kavoura A. Evaluating How 'Smart'Brașov, Romania Can Be Virtually via a Mobile Application for Cultural Tourism. Sustainability. 2020 Jul 1;12(13):5324. https://doi.org/10.3390/su12135324

5. Devagiri JS, Paheding S, Niyaz Q, Yang X, Smith S. Augmented Reality and Artificial Intelligence in industry: Trends, tools, and future challenges. Expert Systems with Applications. 2022 Nov 30; 207:118002. https://doi.org/10.1016/j.eswa.2022.118002

6. Zhang B, Romainoor NH. Research on artificial intelligence in new year prints: the application of the generated pop art style images on cultural and creative products. Applied Sciences. 2023 Jan 13;13(2):1082. https://doi.org/10.3390/app13021082

7. Lavdas AA, Mehaffy MW, Salingaros NA. AI, the beauty of places, and the metaverse: beyond "geometrical fundamentalism". Architectural Intelligence. 2023 Mar 28;2(1):8. https://doi.org/10.1007/s44223-023-00026-z

8. Pisoni G, Díaz-Rodríguez N, Gijlers H, Tonolli L. Human-centered artificial intelligence for designing accessible cultural heritage. Applied Sciences. 2021 Jan 19;11(2):870. https://doi.org/10.3390/app11020870

9. Gupta S, Kamboj S, Bag S. Role of risks in the development of responsible artificial intelligence in the digital healthcare domain. Information Systems Frontiers. 2023 Dec 1:1-8. https://doi.org/10.1007/s10796-021-10174-0

10. Gong Y. Application of virtual reality teaching method and artificial intelligence technology in digital media art creation. Ecological Informatics. 2021 Jul 1; 63:101304. https://doi.org/10.1016/j.ecoinf.2021.101304

11. Benvenuti M, Cangelosi A, Weinberger A, Mazzoni E, Benassi M, Barbaresi M, Orsoni M. Artificial intelligence and human behavioral development: A perspective on new skills and competences acquisition for

the educational context. Computers in Human Behavior. 2023 Nov 1; 148:107903. https://doi.org/10.1016/j.chb.2023.107903

12. Ameen N, Sharma GD, Tarba S, Rao A, Chopra R. Toward advancing theory on creativity in marketing and artificial intelligence. Psychology & marketing. 2022 Sep;39(9):1802-25. https://doi.org/10.1002/mar.21699

13. Rajagopal NK, Qureshi NI, Durga S, Ramirez Asis EH, Huerta Soto RM, Gupta SK, Deepak S. Future of Business Culture: An Artificial Intelligence-Driven Digital Framework for Organization Decision-Making Process. Complexity. 2022;2022(1):7796507. https://doi.org/10.1155/2022/7796507

14. Verganti R, Vendraminelli L, Iansiti M. Innovation and design in the age of artificial intelligence. Journal of product innovation management. 2020 May;37(3):212-27. https://doi.org/10.1111/jpim.12523

15. Yang W. Artificial Intelligence education for young children: Why, what, and how in curriculum design and implementation. Computers and Education: Artificial Intelligence. 2022 Jan 1; 3:100061. https://doi.org/10.1016/j.caeai.2022.100061

16. Arias-Pérez J, Vélez-Jaramillo J. Ignoring the three-way interaction of digital orientation, Not-invented-here syndrome and employee's artificial intelligence awareness in digital innovation performance: A recipe for failure. Technological Forecasting and Social Change. 2022 Jan 1; 174:121305. https://doi.org/10.1016/j.techfore.2021.121305

17. Van Esch P, Stewart Black J. Artificial intelligence (AI): revolutionizing digital marketing. Australasian Marketing Journal. 2021 Aug;29(3):199-203. https://doi.org/10.1177/18393349211037684

FINANCING
The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION
Data curation: Yue Zhuo.
Methodology: Hongli Pang.
Supervision: Hongli Pang.
Drafting - original draft: Yue Zhuo.
Writing - proofreading and editing: Yue Zhuo, Hongli Pang.