Contemporary interpretation of the elegance of Minoan costume

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ABSTRACT – REZUMAT

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The article addresses a highly relevant topic: the application of artificial intelligence (AI) to the design of Minoan-inspired clothing by transforming fashion illustrations into photorealistic visualisations of physical, wearable garments. Advanced AI systems have been used to develop innovative and practical fashion design solutions that capture the timeless elegance of Minoan costumes while giving them contemporary flair. The study includes an application-based analysis of five affordable AI systems that can transform fashion drawings into photorealistic images. A comparative analysis highlights the observed differences in colours and shapes between the original fashion drawings and the AI-generated models. The effectiveness of these AI systems was validated through a survey and principal component analysis. The results obtained have practical implications in areas such as fashion design, custom clothing production, sustainable fashion, marketing and the training of professionals in this field.

Keywords: *ancient Greek clothing, Minoan costume, AI tools, fashion design, principal component analysis*

Interpretarea contemporană a eleganței costumului minoic

Articolul abordează o temă de mare actualitate: aplicarea inteligenței artificiale (IA) în proiectarea vestimentației inspirate din costumul minoic, prin transformarea schițelor de design vestimentar în vizualizări fotorealiste ale unor creații vestimentare reale și purtabile. Sisteme avansate de inteligență artificială au fost utilizate pentru a dezvolta soluții inovatoare și practice de design vestimentar, care surprind eleganța atemporală a costumelor minoice, conferindu-le totodată un aspect contemporan. Lucrarea prezintă o analiză practică a cinci platforme de inteligență artificială accesibile, capabile să convertească schițele de design vestimentar în imagini fotorealiste. Analiza comparativă evidențiază diferențele de culoare și formă dintre schițele de design vestimentar originale și modelele generate cu ajutorul IA. Eficiența acestor sisteme a fost evaluată prin aplicarea unui chestionar online și prin analiza componentelor principale. Rezultatele obținute au implicații practice în domenii precum designul vestimentar, producția de îmbrăcăminte personalizată, moda sustenabilă, marketingul și formarea specialiștilor din acest domeniu.

Cuvinte-cheie: *îmbrăcăminte greacă antică, costum minoic, instrumente bazate pe inteligență artificială, design vestimentar, analiza componentelor principale*

INTRODUCTION

Historical costumes are one of the most frequently used sources of inspiration by fashion designers for the creation of new models and fashion collections [1]. Considering this, the increased interest in our cultural heritage and folk creativity is reflected in fashion design [2, 3]. Successful fashion design involves the study and analysis of the elements of traditional costumes, their symbolism, modern stylisation of ornaments, interrelationship with contemporary fashion trends, and adapting the assembly features of traditional costumes to the creation and modelling of contemporary clothing. According to Dineva [4], the subject of the study will be the elements and their modern interpretation from traditional Balkan costumes.

The Minoan costume is significantly more elaborate and modern compared to most other traditional clothing and symbolises the ancient Greek culture. As a result of extensive research on Minoan costume, it has been found that complexity, embroidery with stripes, fringes, jewels, ornaments, and colours are some of the main characteristics of this ancient civilisation, which is also confirmed by the existing murals and ceramics. Although much of the literature on Minoan costumes deals with ethnological and design considerations, a summary of these garments with ontological descriptions and numerical expressions is still necessary for these costumes to be easily accepted for modern fashion use [5].

The main materials of Minoan costumes are linen and wool. The distinctive features of the female Minoan costume are an X-shaped silhouette (hourglass);

Bell-shaped skirt made of stripes, checks, diamonds, and stripes with embroidery; fitted, hip-length or longer top, elbow-length sleeves, deep neckline revealing the breasts (it is questionable whether the Minoans always wore bare breasts or only revealed them at festivals); fastens with a belt around the waist; Short apron; Hat: high, pointed, beret, turban, triangular, with decoration: rosettes, feathers, ribbon [6].

Although the historical context of Minoan costume is extensive and this costume has enormous design potential in modern times, there is little research on consumer opinions regarding the integration of these elements into contemporary fashion. While the fashion industry continues to open up to artificial intelligence (AI) technologies, some of which are already offering notable advances in trend forecasting, inventory management, and personalised experiences, AI, particularly in modelling diffusion-based imaging systems, still has relatively unexplored potential in the field of fashion design and merchandising [7, 8].

Capable of generating highly realistic and creative fashion images, these AI systems have enormous potential to revolutionise the design process, marketing strategies and virtual customer experience.

Given the current state of scientific and technological development, the academic community and industry experts are increasingly interested in AI text-to-image generators based on machine learning and modelling techniques [9, 10]. These techniques, which translate textual descriptions of images into realistic, detailed paintings, have opened up entirely new avenues of creativity in fashion, advertising, and entertainment. Researchers' interest in using these tools to support design processes and creative workflows is growing, but most existing AI design developments remain in the digital domain, and very few of them translate designs into physical products.

Advanced AI rendering technology allows users to input initial images along with text descriptions representing fabrics and styles. This innovation leads to creativity, efficiency, and improvement in the work results of designers [11].

There is a lack of sufficient research and solid practical applications to translate AI designs into a photorealistic visualisation of a physical, wearable garment. Overcoming these gaps will help realise the full potential of AI in the fashion industry. The simulation of materials and fabrics, the integration of AI processes into manufacturing and the inclusion of real-time user feedback for customisation ensure that the methods used are not only effective but also sustainable. This study aims to contribute to the field of AI applications in fashion design by incorporating advanced systems to develop innovative and practical solutions that blend the timeless elegance of Minoan costumes with a contemporary sense of modernity.

MATERIAL AND METHODS

The integration of elements from Minoan costumes into modern clothing and textiles can be achieved in various ways, including garment and accessory manufacturing, pattern creation and design, fashion illustration, 3D modelling, and online clothing customisation simulators [7]. This approach shows how these researched costume elements and motifs can be adapted for contemporary fashion. The selected methods include fashion drawing (sketching), online clothing simulation and the use of AI.

Table 1 provides an overview of the online tools used to create photorealistic images. Additionally, a tool used for further image processing, particularly background removal, is highlighted. This step improves image comparability, as each AI generator applies its own default background, which may not match the intended presentation.

The primary colours in the clothing patterns are defined by an RGB colour model. They are then converted into Lab for the calculation data (observer 2º and illuminance D65). The colour difference (ΔE) was determined. It varies in the range of 0–100; The closer it is to 0, the more similar the colours of the compared samples are, and the closer it is to 100, the more different they are. The naked human eye distinguishes colours with $\Delta E > 20$ [12].

Table 1

ONLINE TOOLS USED IN THIS STUDY				
Abbreviation	**Name**	**Internet link**	**Accessed**	**Description**
-	Remove bg	https://www.remove.bg	18.05.2024	Removes background from image
NA	NewArc ai	https://www.newarc.ai	22.06.2024	Turns any sketch into a photo using an AI tool
OA	OpenArt ai	https://openart.ai	11.07.2024	Turns any sketch into a photo using an AI tool
AR	Architect Render ai	https://app.architectrender.com	28.07.2024	Turns any sketch into a photo using an AI tool
PP	Petalica Paint	https://petalica.com	19.07.2024	Colorize sketches
RW	Runway ML	https://app.runwayml.com	29.07.2024	Turns any sketch into a photo using an AI tool

$$\Delta E = (L_c - L_a)^2 + (a_c - a_a)^2 + (b_c - b_a)^2 \quad (1)$$

where L_c, a_c, b_c are colour components of fashion drawings; L_a, a_a, b_a – colour components of AI-generated models.

Colour matching between fashion drawings and AI-generated dresses is crucial to ensure precision, accuracy, and quality of design, bringing the final products as close as possible to the original vision. AI tools offer the opportunity to refine the creative process by addressing the inconsistencies that need to be corrected.

A total of five basic formulas were used to determine silhouette shape coefficients [13]. They have the following form:

$$K_1 = \frac{A}{A_{ideal}} \quad (2)$$

$$K_2 = \frac{A}{A_{mr}} \quad (3)$$

$$K_3 = \frac{D - d}{D} \quad (4)$$

$$K_4 = \frac{d}{D} \quad (5)$$

$$V = \frac{4}{3}\pi\frac{D}{2}\left(\frac{d}{2}\right)^2 \qquad K_5 = \frac{3V}{4\pi Dd^2} \quad (6)$$

where d is a minor axis of the silhouette; D – a major axis of the silhouette; P – the perimeter; A – the area; A_{ideal} – the ideal area calculated along the major and minor axes of the silhouette. A_{mr} is the area of the rectangle enclosing the silhouette. V was calculated from the major and minor axis data.

Comparing fashion drawings to AI-generated clothing shapes, shape factors K1 to K5 describe shape characteristics objectively and quantitatively. K1 and K2 determine the efficiency of the area in relation to ideal shapes and bounding rectangles and thus show consistency in design and use of space. K3 and K4 determine the degree of elongation and roundness and can help assess proportions and symmetry. K5 describes the three-dimensional occupation of space and the volumetric deviation from the ideal shape.

A Euclidean distance was calculated between the obtained shape factor values for the sketch and those from the AI-generated ones. The Euclidean distance is determined by the following formula:

$$d(k_s,k_{ai}) = \sqrt{(k_s - k_{ai})^2} \quad (7)$$

where k_s is a coefficient value of fashion drawings and k_{ai} – a coefficient value of an AI-generated model.

The survey was conducted using Google Forms (Google Inc., Googleplex, Mountain View, California, U.S.) in compliance with all the requirements of the ethical code of Trakia University, Stara Zagora, Bulgaria [14].

According to Mladenov [15], the principal component analysis (PCA), used to compare clothing samples and objects generated by AI tools, involves the creation of an orthogonal coordinate system in which the axes are ordered according to the corresponding principal component and variations of the original data. If the covariance matrix is diagonal, it means that the variables are independent. Otherwise, the data can also be displayed at its mean squared error by selecting the variable with the highest variance. The number of principal components was determined according to the criterion that it should describe more than 95% of the variance of the experimental data.

RESULTS

Photorealistic representation of fashion drawings

Six fashion drawings of Minoan-style dresses are offered. Figure 1 shows the main dress patterns based on Minoan costume.

Model M1 is a multi-layered hourglass dress with brown colours, short sleeves, and a high neckline. Model M2 represents a fitted silhouette with an accentuated waist, achieved through a colourful decorative belt. The small sleeves are attached to a bustier, while the multi-layered blue skirt extends

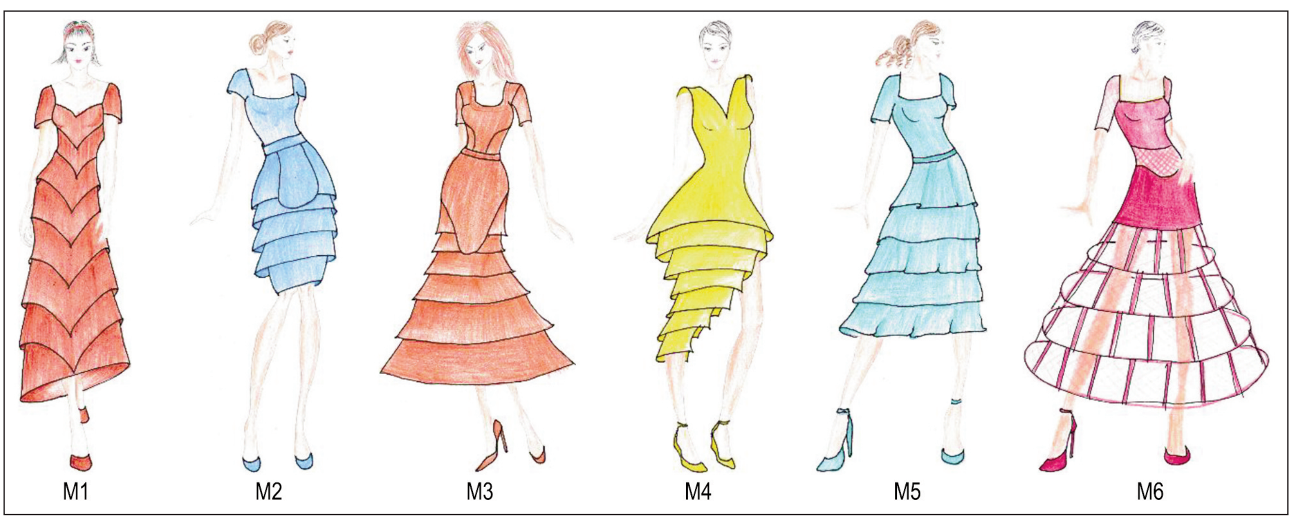

Fig. 1. Main fashion drawings

below the knee. An apron around the waist elegantly complements the ensemble. The Model M3 is very fitted; the neckline is deep and is framed by a decorative band. The hips are defined by a top skirt layer that reaches mid-thigh, highlighting the fitted waist and emphasising femininity. Below this, five additional layers progressively expand downward, creating a flowing and liberated silhouette. Model M4 is asymmetrical and multi-layered in a warm yellow colour combination with a deep plunging neckline. Model M5 has an X-shaped silhouette and combines the multicoloured skirt with the monochrome of the bustier. The deep, square neckline is adorned with Minoan motifs, while the short sleeves emphasise the neckline. The upper part of the dress is fitted, and the lower part is multi-layered, with the first layer having the possibility of being removed as a type of apron. Model M6 features a fitted silhouette at the top, with elegant mesh sleeves extending to mid-arm. The strongly cut square neckline accentuates femininity, and the waist is highlighted by a small mesh panel with a symbolic round shape. This transitions into a short skirt that follows the hips, forming the base of the richly patterned full skirt. Each successive layer expands with staggered elements, adding playfulness and elegance to the final silhouette. The dark cherry colour palette enhances the outfit's vibrancy and charm.

Table 2 presents the auxiliary descriptions (prompt) for generating photorealistic models of dresses. Model colours are also set as text descriptions. Some prompts are automatically generated by NewArc.ai, supplemented by the authors.

Figure 2 shows the models generated using NewArc.ai. The M1 model accurately represents the women's dress in an almost exact colour palette, with the correct layering of the model. An AI tool added decorations to the fabric. M2 follows the silhouette and colour, forgoing the small removable apron but adding a patch to the front of the skirt on the top layer of the dress. The model M3 respects the silhouette; the large neckline and narrow sleeves are emphasised; It is fitted around the waist. Here, the small apron is more clearly expressed. In the model M4, attention is paid to the warm yellow colour and the asymmetrical, multi-layered lower part of the dress, which is strongly fitted and has a sharp neckline, but the straps are very thin. The model M5 retains all the basic colours and shapes of the original fashion design. In the model M6, the transparency of the skirt is retained, but not completely. Floral elements that were not present in the original fashion drawing were added.

Table 2

IMAGE SUPPORTING DESCRIPTIONS (PROMPTS)

Model	Prompt
M1	Red evening gown, chevron pattern, sweetheart neckline, short sleeves, floor-length, tiered design, form-fitting silhouette
M2	Blue dress, tiered ruffled skirt, cap sleeves, fitted bodice, square neckline, high bun hairstyle
M3	Elegant coral evening gown, fitted bodice, tiered ruffled skirt, square neckline, short sleeves, cinched waist
M4	Yellow cocktail dress, v-neckline, sleeveless design, tiered ruffled skirt, fitted bodice, ankle-strap high heels
M5	Turquoise tiered dress, square neckline, short sleeves, ruffled layers, fitted bodice, matching high heels
M6	Fashion sketch, pink dress, crinoline structure, fitted bodice with straps, checkered waist detail, high heels, transparent skirt

Fig. 2. Models generated with NewArc.ai

Fig. 3. Models generated with OpenArt.ai

Figure 3 presents the models generated using OpenArt.AI, employing the same auxiliary descriptions as outlined earlier. For Model M2, additional colours were generated on the top and the first layer of the skirt. All models appear clean, without any additional accessories.

The colours of Models M5 and M6 differ slightly from their original fashion drawings. Model M1 adheres to the intended silhouette, but its colours are darker compared to the original design. Model M2 retains the silhouette, but the original colours were not preserved; white and purple were added.

Model M3 accurately maintains the original silhouette. However, the apron's belt has changed colour, making it more prominent and dynamic. Model M4 preserves the original colour palette and shape, and the sectional details are recreated with greater precision compared to outputs from other AI image generators. Model M5 replicates the silhouette, neckline shape, and narrow sleeves, but the colours are lighter and do not closely match the original design. In Model M6, the shape and silhouette align with the original, although the colours are less accurate.

Figure 4 illustrates the models generated using ArchitectRendering.ai, with the same auxiliary descriptions as previously noted. For the models M1 and M5, the AI tool introduced a pattern to the fabric. Additionally, a fashion accessory – a handbag – was added to the M5 model. The other models remain unadorned, without any additional accessories. The skirt of the M6 model is rendered as opaque.

In the model M1, the silhouette and colour are preserved, but a pattern is applied to the fabric. In the case of the model M2, the silhouette, shape, and colour are faithfully represented; however, the apron lacks a belt, which may affect its mobility. The models M3 and M4 retain all elements of the original fashion design. For the model M5, the AI generated larger drapes than those in the original image, and the sleeves appear wider than in the initial fashion drawing. Lastly, in the model M6, the transparency characteristic of the original design is successfully maintained.

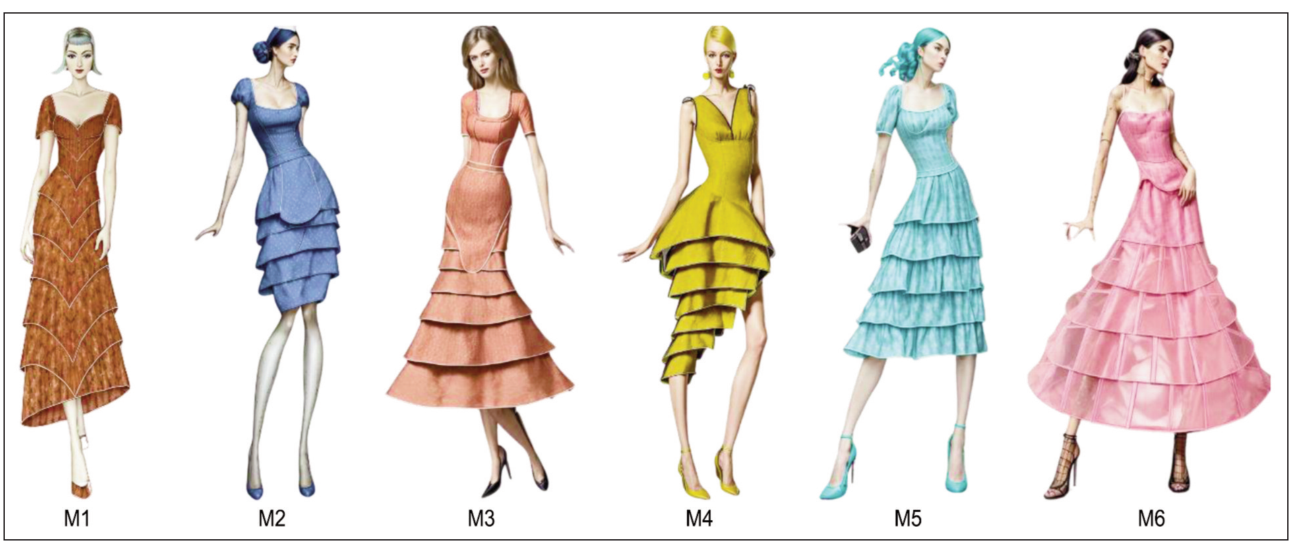

Fig. 4. Models generated with ArchitectRendering.ai

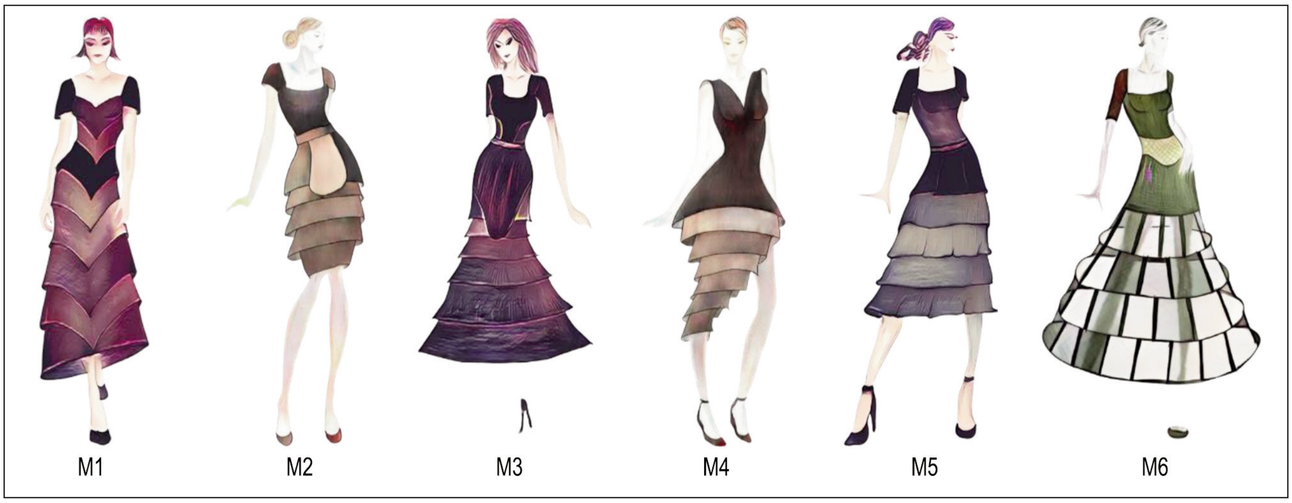

Fig. 5. Models generated with Petalica Paint

Figure 5 shows the models created with Petalica Paint. The same auxiliary descriptions as above are used. All models hold the silhouettes and original models, but the colour combinations do not match.

Figure 6 shows the models generated with RunWayML. The same auxiliary descriptions as above are used. The fabrics generated are clean, without patterns. In models M1 and M4, the elements specific to the Minoan costume are highlighted. In model M2, white and golden skirt colours have been added. Also, as in the original fashion design, model M6 features a see-through skirt. The models are clean, without added accessories. Model M1 has outlines in the layers of the dress, which may not be well received by some users. In model M2, the silhouette, main colour, and mobility of the apron are preserved, but the last three layers of the multi-layered dress do not match the original. In model M3, there is a complete match with the original in silhouette, belt, and mobility of the apron, but it does not correspond in colour. Model M4 has added contours at the ends of the asymmetric dress, which may not be well received by some users. Model M5 differs only in colour from the original fashion drawing. Model M6 retains the transparency of the skirt and sleeves, but the model is too stylised.

Figure 7 shows the primary colours used in fashion drawings and AI-generated images. Visual colour analysis shows that these AI-generated images match the underlying fashion drawings. There is no match at all with Petalica Paint. Additionally, the model M6 generated with RunWayML shows a significant difference in the base colour generated. To illustrate these colour differences in more detail, numerical analysis is required.

Table 3 shows values from the lab colour model for the primary colours presented. Colour component values from the Lab model show that the NewArc.ai-generated objects predictably have the closest match to the source fashion drawings, performing strongly for M3 and M4. OpenArt.ai shows sufficient accuracy, but with deviations for M2, M3, and M6.

ArchitectRendering.ai only performs well on M4, deviating from many other models. Significant inconsistencies are observed in the models generated with Petalica Paint and RunWayML, more evident in the

Fig. 6. Models generated with RunWayML

models M2, M3, and M6. In all AI instruments, significant deviations in the lab values of the colour components are observed for the M6 model.

Table 4 shows the colour difference between the fashion drawings and the AI-generated dress models. The colour difference analysis shows that NewArc.ai

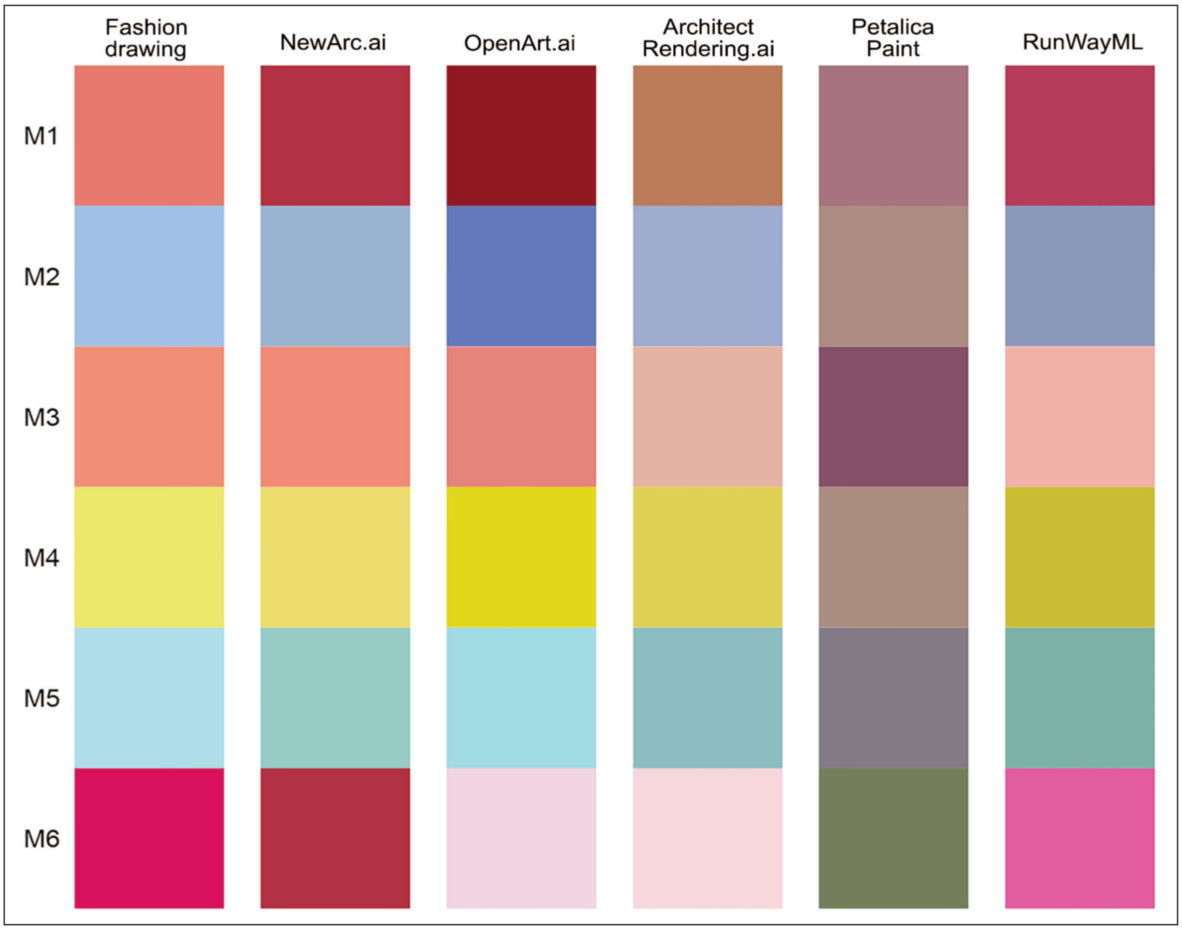

Fig. 7. Main colours from fashion drawings and AI-generated images

Table 3

LAB VALUES OF MAIN COLOURS							
Source	Model / Colour	M1	M2	M3	M4	M5	M6
Fashion drawing	L	57.81	70.55	62.92	86.66	79.67	47.99
	a	53.52	–10.65	49.83	–0.63	–27.61	73.03
	b	34.41	–41.82	37.76	64.93	–14.81	24.66
NewArc.ai	L	41.05	60.66	61.94	82.06	67.63	63.25
	a	54.56	–7.24	50.23	3.26	–23.71	36.47
	b	28.21	–23.36	35.9	60.17	–3.36	7.11
OpenArt.ai	L	28.34	40.79	58.39	77.34	76.49	81.53
	a	50.1	5	46.57	–2.32	–27.38	20.42
	b	32.22	–46.11	27.49	78.25	–15.33	–8.51
Architect Rendering.ai	L	50.74	58.66	68.49	75.94	62.2	82.66
	a	29.79	–1.74	22.78	1.99	–19.94	18.07
	b	31.79	–24.72	18.41	62.01	–8.68	0.73
Petalica Paint	L	44.68	50.95	31.89	50.66	42.13	41.57
	a	24.42	14.38	25.44	13.14	3.3	–7.84
	b	2.12	11.76	–3.38	13.08	–5.22	17.52
RunWayML	L	41.35	51.59	70.33	67.1	57.65	53.25
	a	52.21	–2.54	32.87	0.88	–23.8	63.23
	b	17.94	–21.89	19.12	62.22	0.43	–5.07

Table 4

COLOUR DIFFERENCE ΔE BETWEEN FASHION DRAWINGS AND AI-GENERATED MODELS						
Source / Model	**Sketch**	**NewArc.ai**	**OpenArt.ai**	**Architect Rendering.ai**	**Petalica Paint**	**RunWayML**
M1	0	17.88	**31.66**	**24.12**	**33.39**	17.82
M2	0	19.58	**30.77**	**22.61**	**65.89**	**21.68**
M3	0	2.22	12.48	**31.85**	**56.29**	**27.82**
M4	0	6.51	15.89	11.11	**65.28**	20
M5	0	14.06	3.2	**21.97**	**45.75**	**24.68**
M6	0	**40.31**	**72.69**	**73.3**	**81.93**	**32.39**

has a closer colour match to the original fashion drawings than the other AI tools, especially for the M3 and M5 models. OpenArt.ai performs well on the model M5, although there are significant deviations for the M6 model. ArchitectRendering.ai has moderate colour accuracy, but there is a slight colour difference for the M4 model. A significant colour difference is observed in all models generated with Petalica Paint, which is greatest in models M2, M4, and M6. RunWayML shows average results. For M1 and M5, the results are more accurate, but for M3 and M6, there are serious deviations. As for the colour reproduction for the model M6, all the AI tools do not show a sufficiently accurate result.

Table 5 shows the results of determining the shape coefficients. Comparing the coefficient values, it becomes obvious that most AI tools do reproduce the shapes of models M1 to M5, and their coefficients are very close to those in the original fashion drawings. However, all instruments lack sufficient accuracy in the model M6, showing significant biases, especially for the K1 and K2 coefficients. In most models, OpenArt.ai and ArchitectRendering.ai show the greatest accuracy, while Petalica Paint and RunWayML show some differences, although overall,

Table 5

COEFFICIENTS OF FORM										
Source	**Fashion drawing**					**NewArc.ai**				
Coefficient / Model	K1	K2	K3	K4	K5	K1	K2	K3	K4	K5
M1	0.83	0.65	0.71	0.29	0.13	0.93	0.73	0.76	0.24	0.13
M2	0.59	0.47	0.70	0.30	0.13	0.66	0.52	0.76	0.24	0.13
M3	0.69	0.54	0.63	0.37	0.13	0.70	0.55	0.68	0.32	0.13
M4	0,76	0,59	0,68	0,32	0.13	0.82	0.64	0.72	0.28	0.13
M5	0.59	0.47	0.62	0.38	0.13	0.62	0.49	0.65	0.35	0.13
M6	0.77	0.60	0.37	0.63	0.13	0.52	0.41	0.63	0.37	0.13
Source	OpenArt.ai					ArchitectRendering.ai				
Coefficient / Model	K1	K2	K3	K4	K5	K1	K2	K3	K4	K5
M1	0.92	0.73	0.76	0.24	0.13	0.89	0.70	0.73	0.27	0.13
M2	0.60	0.47	0.74	0.26	0.13	0.67	0.52	0.71	0.29	0.13
M3	0.71	0.56	0.68	0.32	0.13	0.70	0.55	0.69	0.31	0.13
M4	0.80	0.63	0.71	0.29	0.13	0.77	0.60	0.72	0.28	0.13
M5	0.66	0.52	0.66	0.34	0.13	0.62	0.49	0.64	0.36	0.13
M6	0.15	0.12	0.62	0.38	0.13	0.37	0.29	0.69	0.31	0.13
Source	Petalica Paint					RunWayML				
Coefficient / Model	K1	K2	K3	K4	K5	K1	K2	K3	K4	K5
M1	0.82	0.64	0.58	0.42	0.13	0.93	0.73	0.76	0.24	0.13
M2	0.52	0.41	0.64	0.36	0.13	0.54	0.42	0.75	0.25	0.13
M3	0.68	0.53	0.65	0.35	0.13	0.70	0.55	0.62	0.38	0.13
M4	0.73	0.57	0.69	0.31	0.13	0.81	0.64	0.70	0.30	0.13
M5	0.54	0.43	0.65	0.35	0.13	0.64	0.50	0.67	0.33	0.13
M6	0.31	0.24	0.56	0.44	0.13	0.51	0.40	0.56	0,.44	0.13

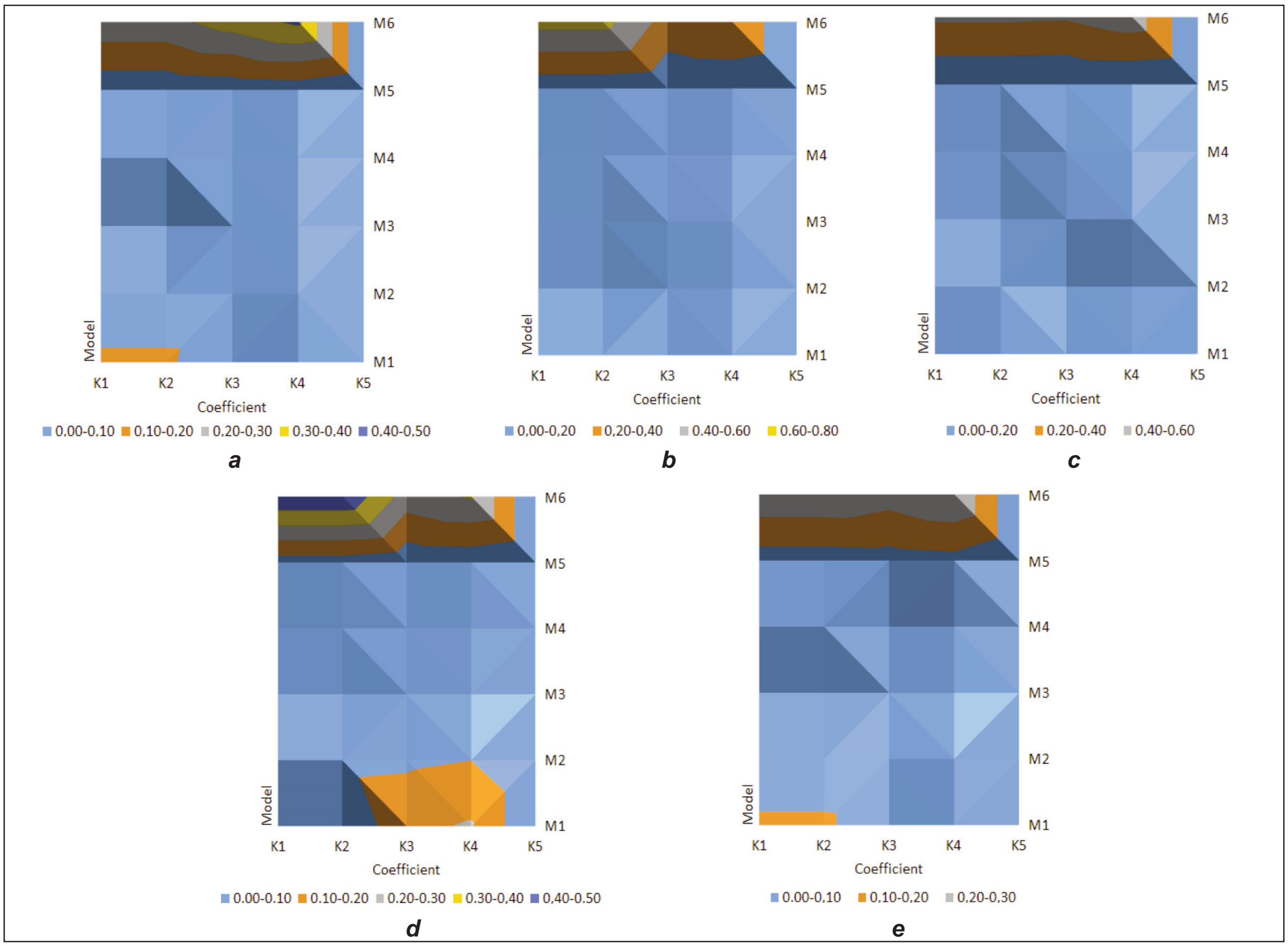

Fig. 8. Euclidean distances between fashion drawings and AI-generated models: *a* – NewArc.ai; *b* – OpenArt.ai; *c* – ArchitectRendering.ai; *d* – Petalica Paint; *e* – RunWayML

relatively close replications are obtained for most models.

Figure 8 plots the Euclidean distances between the shape factors of the fashion drawings and those of the AI-generated models. The Euclidean distances for the AI-generated dress patterns with respect to the original ones show that in most cases, the AI tools can reproduce the shapes of the M1 to M5 patterns with fairly low distances and therefore a significant match. In parallel, all instruments have significant difficulties with M6, showing larger distances and therefore larger differences with the original. In most of the models, OpenArt.ai and ArchitectRendering.ai perform well enough, except when working with M6. This means that while these current AI tools are able to reproduce simple or more common forms of fashion drawings, they struggle with more complex or unique designs like the M6.

Survey results

A survey was conducted on users' opinions about the created photorealistic dress models. Figure 9 shows an overview of the survey form used. The survey involved 73 respondents who selected the clothing models a total of 393 times (with the possibility of selecting more than one model).

Table 6 shows the results of the survey. The number of selected models is indicated. Dress models show that they are selected differently depending on which AI tool they were generated with. In this case, it is noticeable that M1 is most often selected by NA (31 times) and by RW (17 times), thus showing a preference for models generated with these two tools. Again, although M2 generated with NA is also more frequently selected (30 times), it does not share the same position among all other instruments. While the average choice in most instruments is M3, M4, and M5, the top choice is NA, a testament to the dominant role it plays. M6 is less popular overall but has a notable PP selection (14 times), indicating a specific colour or shape preference unique to PP.

Figure 10 shows the results of a principal component analysis. The two principal components describe

Table 6

SURVEY RESULTS – NUMBER OF RESPONSES

Model / AI tool	M1	M2	M3	M4	M5	M6
NA	31	30	18	27	27	25
OA	9	12	12	16	13	11
AR	6	8	13	9	15	12
PP	4	5	6	5	6	14
RW	17	7	9	6	12	8

Note: NA – NewArc.ai; OA– OpenArt.ai; AR – Architect Render.ai; PP – Petalica Paint; RW-Runway ML.

Fig. 9. Survey form – general view

96.09% of the variance in the analysed data. Dress patterns M1 to M6 are more or less related to the two main components. M1 and M5 fit the main trends in the data due to their positive relationship with PC1 and therefore reproduce common characteristics or styles. In contrast, M6 exhibits a negative relationship with PC1 and PC2, indicating unique or distinct characteristics that none of the other models have. M3 and M5 have high positive principal component values at PC2. Therefore, they bring up different points of variability associated with quite different design elements. The AI tools also show a non-uniform scatter in the principal components plot. NA is strongly positively correlated with PC1, which has a dominant trend or influence in the data set as a result of its capabilities and wider selection by users. However, PP is strongly negatively correlated with PC1, which means that it represents the opposite trend. On the other hand, RW and AR, respectively positively and negatively correlated with PC2, are related to very different aspects of variation and thus can be used for some specific tasks or functions.

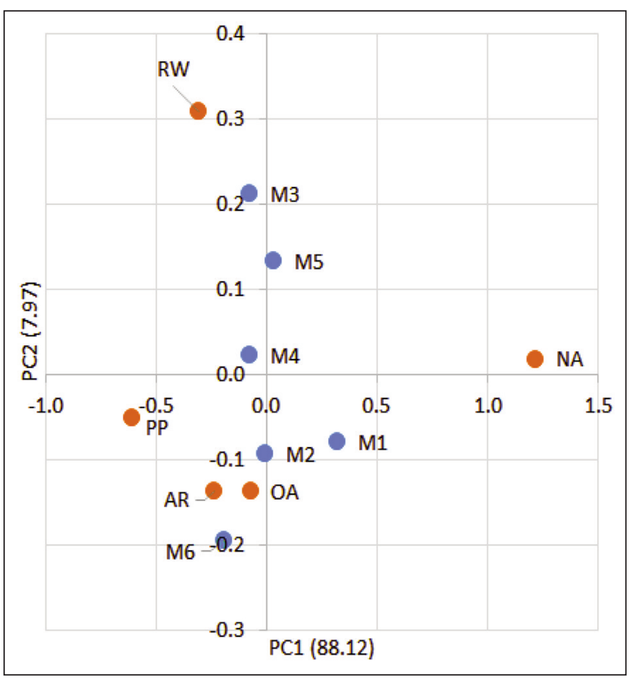

Fig. 10. PCA of survey results: NA – NewArc.ai; OA – OpenArt.ai; AR – ArchitectRender.ai; PP – PetalicaPaint; RW – Runway.ML

A comparative analysis of AI tools

Table 7 below compares the AI tools used on key performance indicators for generating photorealistic images. NewArc.ai matches the closest colour equivalent to the original designs for M3 and M5, with high shape accuracy and low Euclidean distances, making it the most preferred tool, especially for M1 and M2. OpenArt.ai, while reasonably accurate to colours with minor deviations, especially in M2, M3, and M6, describes shape well at small distances; however, it is generally averaged over user choice, correlating positively with both PC1 and PC2.

ArchitectRendering.ai has average colour accuracy and is best with M4. It maintains high shape accuracy, low Euclidean distances, and average user choice, with a positive correlation with PC2, indicating that it is a suitable tool in certain design variations. On the other hand, PP produces highly divergent colours, primarily in the M2, M4, and M6 models, while the differences according to the shape factors are larger and the Euclidean distances are larger too, and it is the least selected tool overall. It is also strongly negatively correlated with PC1; therefore, very often it shows the opposite trend compared to NA.

Table 8 presents a summary of how successful the corresponding AI tool was in realising photorealistic models for fashion drawings M1 to M6. NewArc.ai performs well on models M1 to M5, but quite poorly on M6. OpenArt.ai performs well on models M1, M3, M4, and M5, but encounters problems with M2 and M6. ArchitectRendering.ai does well with models M1 through M5, as is the case with other tools; however, every tool fails when it comes to the M6 model. For PP, poor performance is seen in all models, hence large deviations in accuracy. RW does well with the

Table 7

BENCHMARKING THE RESULTS SHOWN BY AI TOOLS					
AI Tool	**Colour difference**	**Shape coefficients**	**Euclidean distances**	**Survey results**	**Principal component analysis**
NewArc.ai (NA)	The closest match for M3 and M5	High accuracy, minor deviations in M6	Low distances for M1-M5, high for M6	Most selected, especially for M1 and M2	Strongly positively correlated with PC1, indicating a strong influence
OpenArt.ai (OA)	Sufficient accuracy, deviations in M2, M3 and M6	High accuracy but minor deviations in M6	Low distances for M1-M5, high for M6	Average selection, performs well for the M5	Positive correlation with PC1 and PC2 indicates variability
Architect Rendering.ai (AR)	Moderate colour accuracy, best for M4	High accuracy, minor deviations in M6	Low distances for M1-M5, high for M6	Average selection, good for M4	Positive correlation with PC2 is associated with specific design variations.
Petalica Paint (PP)	Significant colour differences in M2, M4 and M6	Variations were observed in M6	Larger distances indicate more deviations from the original	Least selected overall, but noticeable for the M6	Strong negative correlation with PC1, indicating the opposite trend of NA

Table 8

COMPARATIVE ANALYSIS OF THE EFFECTIVENESS OF PHOTOREALISTIC REPRODUCTION OF FASHION DRAWINGS						
AI Tool	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
NewArc.ai (NA)	Y	Y	Y	Y	Y	N
OpenArt.ai (OA)	Y	N	Y	Y	Y	N
ArchitectRendering.ai (AR)	Y	Y	Y	Y	Y	N
Petalica Paint (PP)	N	N	N	N	N	N
RunWayML (RW)	Y	N	N	Y	Y	N

Note: Y – yes; N – No.

M1, M4, and M5 models but poorly with the M2, M3, and M6. This means that most of the tools do reasonably well with the uncomplicated designs of M1 through M5, but fail miserably with the more complex designs of M6.

DISCUSSION

Historical costumes have always served as a source of inspiration for fashion designers. According to Pendergast et al. [1], reinterpreting historical elements offers an opportunity for innovation while preserving the memory of the original. According to Kazlacheva et al. [3], the cultural heritage has recently been given a second life. Therefore, interest in the manifestation of folk creativity remains relevant for solving modern design tasks. Dineva [4] examines historical Balkan clothing, and she argues that traditional clothing can offer a range of design elements that are quite applicable in contemporary fashion. A very good example is that of the Minoan costume described by Papadopoulou et al. [5]. For example, the intricate details of Minoan tapestries, including the layering of skirts, embroidery, and colour combinations, are the inspiration for modern clothing. This falls in line with the general trend of incorporating as many elements of historical costumes as possible to create something original and modern.

In adapting historical prototypes to modern costumes, aesthetic requirements are not enough; there is also a mission requirement seeking an understanding of their symbolic meanings. This would therefore include an hourglass silhouette, a bell-shaped skirt in Minoan costume, and an exaggerated headdress that takes on a variety of complex shapes, ending in a plume of feathers or a horn-like projection on the back [6]. Such stylisations can be introduced into contemporary dress collections as a way of continuing the past and expressing a sense of historical continuity and cultural depth. In modernising stylisation, the preservation of historical authenticity is balanced with the introduction of contemporary relevance.

Artificial intelligence (AI) integrated into fashion design brings some significant steps forward in the industry. If we take a closer look at Sun [7] and Zhang et al. [8], regarding AI technologies related to trend forecasting, inventory management, and personalisation, it can be seen that they have truly revolutionised the design and merchandising processes. This was echoed by Liu et al. [9] and Shaheen et al. [10], who say that AI-generated imagery can enhance designer creativity and efficiency with newer ways to experiment with historical elements and therefore lead to innovations in collection building. These guidelines are supplemented and refined in the current development through a benchmarking of AI tools and a survey.

Regarding the different AI tools available, each has its own levels of performance in fashion design. As the results obtained in this article show, NewArc.ai is the clear leader in user preference and quite strong in the M1 and M2 models. This could indicate that this model borrows heavily from designs that would be considered modern. The high positive correlation with PC1 further indicates the dominant influence on fashion trends. The Runway ML tool is mainly preferred for the M1 model. Its correlation with PC2 means that it focuses on different elements of design variation than NewArc.ai. Users prefer the M6 model generated with PetalicaPaint. This means that this AI tool is suitable for certain tastes or other unique design elements that other tools have not been able to capture. OpenArt.ai and ArchitectRender.ai generate a more balanced selection between models, with no one dominating. This is because their correlations with the principal components are different and therefore, they lead to different design results.

CONCLUSION

The present study, therefore, highlights the potential that AI holds in fashion design and how its applications could revolutionise the industry's approach to creativity and, ultimately, responsiveness to consumer preferences. This comparative study aims to explore how blending historical and contemporary patterns with modern technologies could play a crucial role in fashion design. For example, historical costumes, such as those of the Minoan civilisation, can be adapted to contemporary fashion, providing both depth and continuity. Now that all of these concepts are integrated into the process through AI technologies, designers can work more freely and iteratively improve their results. The skills gap across these different AI tools further underscores the need to combine historical inspiration with renewed innovation.

It has been noticed that the preference for AI-generated dress models depends on the specific tool that generated them, where tools like NewArc.ai take a leading role by fitting into the modern design trend. Quantitative analysis shows that models like M1 and M5 include highly preferred design elements, while other models, such as M6, provide preferences for niches with specialised tools such as Petalica Paint.

The principal component analysis has shown that 96.09% of the total variance is covered by the first two components, underlining clear trends and distinctions in the variability of the designs. While some AI tools were aligned positively with dominant or unique aspects in design trends, other strongly relates negatively to the contemporary style in the output and accentuate its unique role.

These findings add to some of the empirical evidence that may contribute to the diverse literature on the diversity of AI-generated designs and how those are received by users. The present study has established the strong influence of AI tools in setting dominant design trends while proving the unique contribution made by niche tools toward diverse creative output.

The results of the present study may be applied to practice in at least the following directions: fashion design, clothes customisation, sustainable fashion, marketing, and professional training. However, significant challenges also remain, with a special emphasis on technological implementation: fabric simulation, integration into production methods, the process of customisation, and ethical treatment of users.

Overcoming these challenges requires further research. Development should be done in enhancing the AI algorithms, prototyping, and testing, integrating AI experts with the fashion industry. Besides, there should be sustainable development and the development of platforms that can facilitate feedback from consumers. Addressing these areas ensures that AI can achieve its fullest potential, bringing innovation, efficiency, and sustainability to the fashion industry.

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