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Between tradition and algorithm: Human–AI co-creation in textile design education and its implications for cultural authenticity

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Article

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Abstract

The rapid integration of generative AI into creative industries has intensified debates about the future of culturally grounded design practice. This study examines how three production conditions (human-only, AI-assisted, and fully autonomous AI) differentially affect the perceived cultural fidelity, creativity, aesthetics, and commercial viability of textile designs rooted in traditional Anatolian kilim motifs, a question with limited prior empirical evidence in design education. Using a within-subjects design, fifteen undergraduate textile design students produced designs under each condition, using a generative AI platform with substantial commercial reach in the Turkish textile sector for the AI-involved conditions. A panel of ten expert evaluators, five academics and five industry designers, rated 45 designs against a seven-criterion rubric under blind conditions.

Cultural fidelity, creativity, originality, and aesthetics differed significantly across conditions (all $p < .05$). Both human-only and AI-assisted designs preserved cultural fidelity at equivalent levels, and both significantly exceeded fully autonomous AI outputs. Paradoxically, fully autonomous AI outputs received the highest scores for creativity and originality, pointing to a trade-off between perceived novelty and cultural coherence. No significant differences emerged for commercial viability, technical feasibility, or compositional integrity, indicating parity across production methods on industrially relevant dimensions. Academic and industry evaluators converged on cultural fidelity judgements while diverging on more subjective aesthetic criteria.

These findings suggest that human involvement acts as a cultural filter that cannot be replicated through textual instruction alone, and that even minimal human intervention, selecting and lightly editing AI-generated variants, is sufficient to preserve culturally identifiable design characteristics. The results have implications for textile design pedagogy, for AI governance in heritage-sensitive industries, and for theorising human–AI co-creation in cultural production contexts.

1. Introduction

Generative artificial intelligence has rapidly become a productive force in the creative industries, enabling the large-scale generation of images, patterns, and design variants at a speed and scale that no individual practitioner can match (Manovich & Arielli, 2024; Voinea, 2025). Within the textile and fashion sector, this transformation is particularly visible: AI-powered design platforms have moved from experimental tools to operational infrastructure, with some platforms now serving a substantial proportion of national markets. In Turkey, the MYTH AI platform — developed by a company with offices in Istanbul, London, and Delhi — has achieved significant market penetration in the textile design sector, offering capabilities that range from text-to-design generation and image-to-design transformation to motif extraction, colour variant generation, and commercial mockup production.

This industrial context creates a distinctive pedagogical challenge. If a single operator can produce in one day what previously required a team of five designers working over six months, the value proposition of formal design education requires urgent renegotiation. At the same time, the implications for cultural

heritage are not straightforward. Traditional textile design traditions — such as the Anatolian kilim, with its rich repertoire of symbolic motifs, colour conventions, and compositional grammars — represent accumulated knowledge that is embodied in practice, transmitted through apprenticeship, and grounded in cultural meaning (Öztaş & Arda, 2025). Whether generative AI can be meaningfully applied to this knowledge domain, or whether it fundamentally transforms or erodes it, is an empirical question that this study addresses.

The study is guided by two theoretical frameworks. **Human–AI co-creation theory** (Sanders & Stappers, 2008; Bødker & Grønbæk, 1991) provides a lens for understanding the collaborative dynamics between human designers and generative systems, treating AI not as a replacement for human creativity but as an active participant in a joint creative process. **Computational creativity theory** (Colton & Wiggins, 2012; Boden, 2004) frames the question of whether and how AI outputs can be evaluated against the same criteria — novelty, value, cultural coherence — applied to human creative work.

Against this backdrop, the present study makes three empirical contributions. First, it provides experimental evidence on the differential effects of human involvement on culturally evaluated design quality. Second, it identifies a creativity–culture trade-off in AI-mediated heritage design that has not previously been documented empirically. Third, it examines how the evaluative standards of academic and industry experts converge and diverge in assessing AI-involved design outputs — a question with implications for both pedagogy and professional practice.

The study was conducted in partnership with MYTH AI under an institutional collaboration agreement, with the platform used as the AI environment across all AI-involved conditions. This affiliation provides ecological validity — participants used a commercially deployed system actively used in the sector — while also raising questions about generalisability that are addressed in the limitations section.

2. Literature Review

2.1. AI in Creative and Design Practice

The integration of AI into creative production has been extensively documented across multiple domains. Generative Adversarial Networks (GANs), diffusion models, and transformer-based architectures have demonstrated the capacity to produce outputs that are visually indistinguishable from human-authored work across a range of aesthetic domains (Bond-Taylor et al., 2022). Within design specifically, AI tools have been applied to logo generation, spatial design, fashion forecasting, and surface pattern development, with user satisfaction studies generally reporting positive evaluations of AI-generated outputs on technical and aesthetic criteria (Wang & Zhang, 2024).

However, the literature has also identified persistent limitations. Most generative models are optimised for visual realism and stylistic consistency rather than for culturally specific meaning (Manovich & Arielli, 2024). The training datasets underlying commercial generative models are typically large-scale internet corpora that may underrepresent non-Western visual traditions, creating systematic biases in generated

outputs (Elfa et al., 2023). This gap between statistical pattern reproduction and cultural knowledge encoding is particularly consequential in heritage design contexts, where motif integrity and symbolic coherence are primary quality criteria.

2.2. Human–AI Co-Creation

Human–AI co-creation refers to collaborative processes in which human and artificial agents jointly contribute to creative outputs, with the nature and extent of each party's contribution varying across the workflow (Sanders & Stappers, 2008). The concept challenges binary framings of AI as either tool or author, positioning it instead as a creative partner whose outputs require human selection, curation, and contextualisation (Manovich & Arielli, 2024; O'Toole & Horvát, 2024). Empirical studies of co-creative processes have shown that human involvement — even at minimal levels — significantly shapes the perceived quality and authenticity of collaborative outputs (Eisenmann et al., 2026).

In design education contexts, co-creative AI tools introduce new complexities around authorship, skill development, and pedagogical scaffolding (Ursu et al., 2024; Siri et al., 2024). Students who use AI tools as creative partners may develop different competency profiles than those trained exclusively in human-centred workflows, with potential gains in efficiency and stylistic range offset by potential losses in foundational technical skills and domain-specific cultural knowledge (Öztaş & Arda, 2025; Lee, 2024).

2.3. Cultural Heritage and Generative AI

The application of generative AI to culturally situated design traditions raises specific concerns that extend beyond general questions of creative quality. Traditional textile systems such as the Anatolian kilim are characterised by *structural grammars* — rule-based compositional systems that govern the spatial relationships between motifs, the semantic associations of symbolic elements, and the cultural protocols of colour use — that are not easily captured in textual descriptions or inferred from visual datasets alone (Öztaş & Arda, 2025). The risk of *cultural deformation* — the unintentional modification or erasure of culturally significant design elements through algorithmic processing — has been identified as a concern in digital heritage contexts (Elfa et al., 2023), though empirical evidence from controlled design studies remains limited.

The present study addresses this gap by providing experimental evidence on the extent to which different levels of human involvement mediate the preservation of cultural fidelity in AI-assisted kilim design. To our knowledge, it is the first study to examine this question within a formal design education context using a commercially deployed generative design platform with documented sector penetration.

3. Methods

3.1. Research Design

The study employed a mixed-methods, within-subjects experimental design. Each participant produced designs under three conditions, enabling individual creative ability to be controlled and ensuring that

observed differences reflect condition effects rather than between-participant variability. The study received prior approval from the relevant institutional ethics committee; details are provided in the Ethics Statement section of the submission system. Student participation was explicitly decoupled from academic assessment.

3.2. Participants

Fifteen undergraduate textile design students (N = 15; M*age* = 21.3, SD = 1.8; 12 female, 3 male) participated voluntarily. All had prior experience with Adobe Photoshop and Illustrator; none had previously used the MYTH AI platform. A separate panel of ten expert evaluators was recruited for the assessment phase: five textile and design academics (faculty-level) and five industry designers with a minimum of three years' professional experience in the fashion and textile sector.

3.3. Design Brief and Motif Set

All participants received an identical brief:

" For Condition 3, all participants entered an identical standardised prompt individually from their own platform accounts, using MYTH AI v4.6 (Text-to-Design module; generation date: 24 July 2026). The standardised prompt was: *"Generate a kilim design on*70 × *105 cm canvas (2:3 ratio) using a fixed five-colour palette (red #9E2A2B, navy #1D3557, cream #F5E7D9, brown #6B4E31, olive green #606C38). Include at least five of the following ten traditional Anatolian motifs: koçboynuzu [ram's horn], elibelinde [hands on hips], bereket [fertility], suyolu [water path], akrep [scorpion], küpe [*earring*], yıldız [eight-pointed star], kurtağzı [*wolf's mouth*], pıtrak [burr], çengel [hook]. Motif forms must be preserved; scale, rotation, reflection, and repetition are permitted. Target consumer: 25–40-year-old sustainability-oriented home textile purchaser."*
Reference images for all ten motifs were provided as a standardised digital file.

3.4. Production Conditions

Table 1 summarises the procedures and tools used across the three production conditions.

Table 1
Production Conditions, Procedures, and Tools

Condition	Procedure	Duration	Tool
Condition 1: Human	Fully human-authored digital design; AI use prohibited	3 hours (single session)	Adobe Photoshop / Illustrator
Condition 2: AI-Assisted	Upload own Condition 1 design to MYTH AI Image-to-Design; receive 4 variants; select 1; apply ≤ 2 edits	1 hour (separate session)	MYTH AI (Image-to-Design)
Condition 3: Full AI	Enter standardised prompt into MYTH AI Text-to-Design; accept output directly	15 minutes (group lab session)	MYTH AI (Text-to-Design)

Condition 2 designs were produced using the MYTH AI "Create Similar" function (*Benzerini Oluştur*; Image-to-Design module, v4.6), applied on 24 July 2026. For Condition 3, all participants entered an identical standardised prompt individually from their own platform accounts. Because MYTH AI employs stochastic generation, each participant received a unique output despite using the same prompt. This approach produced 15 distinct Full AI designs, enabling within-group variability analysis while maintaining prompt consistency. The standardised prompt was: *"Generate a kilim design on a 70×105 cm canvas (2:3 ratio). Use at least five of these Anatolian motifs: koçboynuzu, elibelinde, bereket, suyolu, akrep, küpe, yıldız, kurtağzı, pıtrak, çengel. Preserve original motif shapes; scale, rotate, reflect, and repeat as needed. Central medallion or all-over symmetrical composition. Colours: red #9E2A2B, navy #1D3557, cream #F5E7D9, brown #6B4E31, olive #606C38 only. No gradients, no 3D, no photorealistic textures. 300 DPI PNG output."*

Figure 2 presents representative outputs from each production condition, illustrating the visual characteristics of the designs evaluated in the study.

To minimise order effects, the three production conditions were completed in the sequence Human → AI-Assisted → Full AI, ensuring that the AI-Assisted condition drew on a pre-existing human design.

3.5. Evaluation Procedure

The 45 designs (15 per condition) were anonymised with random alphanumeric codes (T_001–T_045) and presented to evaluators in five counterbalanced ordering variants, ensuring that no evaluator encountered designs in condition-sequential order. Evaluators were blind to condition assignment throughout the rating process.

Each design was rated on seven criteria using a 1–7 Likert scale (1 = very poor, 7 = excellent). The seven evaluation criteria and their operational definitions are presented in Table 2.

Table 2
Evaluation Rubric

Criterion	Operational Definition
Originality	Novel, unexpected, distinctive solution
Aesthetics	Visual appeal and professional quality
Cultural Fidelity	Preservation of Anatolian kilim character in motifs
Commercial Viability	Suitability for serial production and market deployment
Creativity	Surprising quality; original combinations
Technical Feasibility	Compatibility with industrial printing/weaving processes
Compositional Integrity	Balance, rhythm, emphasis, unity

Evaluation materials were distributed as structured Word documents via email. To reduce evaluator fatigue, materials were divided into three sub-sets of 15 designs each, administered across separate sessions within a two-week window. The presentation order within each sub-set was counterbalanced across evaluators.

3.6. Statistical Analysis

Non-parametric statistics were used throughout, given the ordinal nature of Likert-scale data and the modest sample size. Between-condition differences were assessed using Kruskal-Wallis H tests. Significant omnibus effects were followed up with pairwise Mann-Whitney U tests, applying a Bonferroni-corrected significance threshold of $\alpha = .0167$ (0.05 / 3 comparisons). Evaluator group differences (academics vs. industry designers) were examined using additional Mann-Whitney U tests. All analyses were conducted in Python (SciPy 1.11).

Two design observations were missing from the Full AI condition. To retain these observations in the analysis, the missing values were replaced using group-mean imputation based on the corresponding Full AI condition scores. The imputed values were included in the subsequent statistical analyses. This approach was selected as a simple, transparent procedure given the small sample size and the limited number of missing observations. A sensitivity analysis conducted by excluding these two imputed cases yielded consistent results, confirming that the imputation did not alter the significance or direction of the findings

Effect sizes were reported alongside inferential statistics to quantify the magnitude of between-condition differences. For Kruskal-Wallis tests, epsilon-squared (ε^2) was calculated as a measure of effect size. For pairwise Mann-Whitney U comparisons, effect sizes were calculated using the rank-biserial correlation (r_{rb}). Effect sizes were interpreted alongside p-values to distinguish statistical significance from the practical magnitude of observed differences.

4. Results

4.1. Differences Across Production Conditions

Kruskal-Wallis tests revealed statistically significant differences across the three production conditions for four of the seven evaluation criteria: Originality ($H = 23.22$, $p < .001$), Cultural Fidelity ($H = 53.26$, $p < .001$), Creativity ($H = 39.15$, $p < .001$), and Aesthetics ($H = 8.79$, $p = .012$). No significant differences were observed for Commercial Viability ($H = 0.93$, $p = .630$), Technical Feasibility ($H = 0.87$, $p = .648$), or Compositional Integrity ($H = 4.52$, $p = .104$). Descriptive statistics across the three production conditions are presented in Table 3, and mean scores across the seven criteria are illustrated in Fig. 3.

Table 3
Mean Scores (M) and Standard Deviations (SD) by Production Condition

Criterion	Human M (SD)	AI-Assisted M (SD)	Full AI M (SD)	H	p
Originality	4.07 (1.38)	3.85 (1.50)	4.95 (1.04)	23.22	< .001***
Aesthetics	4.00 (1.47)	3.87 (1.54)	4.48 (1.22)	8.79	.012*
Cultural Fidelity	5.44 (1.06)	5.48 (1.04)	4.14 (1.20)	53.26	< .001***
Commercial Viability	4.41 (1.46)	4.08 (1.44)	4.35 (1.35)	0.93	.630 n.s.
Creativity	3.84 (1.38)	3.63 (1.61)	4.98 (0.88)	39.15	< .001***
Technical Feasibility	5.04 (1.21)	4.82 (1.34)	5.06 (1.16)	0.87	.648 n.s.
Compositional Integrity	4.42 (1.57)	4.03 (1.72)	4.71 (0.99)	4.52	.104 n.s.

*Note. * $p < .05$; *** $p < .001$; n.s. = not significant. Bonferroni-corrected threshold for post-hoc: $\alpha = .0167$.*

4.2. Post-Hoc Pairwise Comparisons

4.2.1. Cultural Fidelity

Post-hoc Mann-Whitney U tests with Bonferroni correction revealed no significant difference between the Human and AI-Assisted conditions ($U = 2254$, $p = .749$), while both conditions scored significantly higher than Full AI (Human vs. Full AI: $U = 4613$, $p < .001$; AI-Assisted vs. Full AI: $U = 3856$, $p < .001$). This pattern indicates that even minimal human involvement — selection from AI-generated variants with up to two edits — was sufficient to preserve culturally identifiable kilim characteristics at levels equivalent to fully human-produced work.

4.2.2. Creativity and Originality

Full AI outputs received the highest mean scores on Creativity ($M = 4.98$, $SD = 0.88$) and Originality ($M = 4.95$, $SD = 1.04$), significantly exceeding both Human (Creativity: $U = 1489$, $p < .001$; Originality: $U = 1874$, $p < .001$) and AI-Assisted conditions (Creativity: $U = 1169$, $p < .001$; Originality: $U = 1420$, $p < .001$). No

significant difference was found between Human and AI-Assisted conditions for either criterion (Creativity: p = .410; Originality: p = .409).

4.2.3. Aesthetics

Significant differences in Aesthetics were driven primarily by the contrast between AI-Assisted and Full AI conditions (U = 1790, p = .007). Full AI outputs (M = 4.48) were rated more favourably than AI-Assisted outputs (M = 3.87), while Human outputs (M = 4.00) did not differ significantly from either condition at the corrected threshold.

4.2.4. Non-Significant Criteria

Commercial Viability, Technical Feasibility, and Compositional Integrity did not differ significantly across conditions, indicating that all three production modes yielded outputs perceived as equivalently suitable for market deployment and technical reproduction.

4.3. Evaluator Group Differences

Industry designers assigned significantly higher scores than academics on Originality (M = 4.67 vs. 3.75; p < .001), Aesthetics (M = 4.39 vs. 3.71; p < .001), Creativity (M = 4.40 vs. 3.84; p = .004), and Compositional Integrity (M = 4.65 vs. 4.01; p < .001). No significant difference was found for Cultural Fidelity (p = .872), Technical Feasibility (p = .628), or Commercial Viability (p = .153).

5. Discussion

This study examined how three production conditions — human-only, AI-assisted, and fully autonomous AI — differentially affect expert evaluations of textile surface designs grounded in traditional Anatolian kilim motifs. The findings offer both empirical and theoretical contributions to the growing literature on human–AI co-creation in design education and cultural heritage contexts. Four discussion themes are organised below, each addressing a distinct dimension of the results.

5.1. Human Presence as a Cultural Filter

The most consistent finding of this study concerns Cultural Fidelity. Both Human and AI-Assisted conditions produced designs rated significantly higher than Full AI outputs - and the two conditions did not differ from each other. This equivalence suggests that the *threshold of human involvement required to preserve cultural integrity is low*: selection of one variant from four, followed by no more than two edits, was sufficient to maintain culturally recognisable kilim characteristics at levels indistinguishable from fully human-authored work.

This finding resonates with Manovich and Arielli's (2024) conceptualisation of AI as an instrument of stylistic augmentation rather than independent authorship. Within a co-creation framework (Sanders & Stappers, 2008), the human designer functions as a *cultural custodian* — selecting, filtering, and ratifying outputs against an internalised repertoire of domain-specific knowledge that the AI system does not

possess. The results suggest that this custodial function can be exercised efficiently, but cannot be fully delegated.

These findings complicate the notion that generative systems can autonomously reproduce culturally situated aesthetics through textual description alone. The detailed prompt used in Condition 3 included motif names, colour codes, compositional guidelines, and target audience specifications — yet the resulting outputs were judged significantly less faithful to Anatolian kilim traditions. This gap between *described knowledge* and *embodied cultural knowledge* points to a fundamental limitation of large-scale generative models in heritage design: they can approximate the visible surface of a tradition without internalising its structural logic or symbolic grammar (Öztaş & Arda, 2025).

It should be noted that AI-Assisted outputs, like Full AI outputs, are computationally generated in their entirety; the distinction lies not in the generation mechanism but in the human-authored seed input and the subsequent curatorial selection and editing, consistent with a co-creation framework in which the human functions as filter rather than manual executor.

5.2. The Creativity Paradox: Novelty Without Cultural Grounding

Full AI outputs received the highest scores on Creativity and Originality - a counterintuitive finding that demands careful interpretation. We propose that this reflects a "cultural uncanny" effect: expert evaluators, familiar with established kilim aesthetics, perceived the deviations introduced by autonomous AI generation as surprising and unexpected, qualities that operationally map onto the creativity and originality criteria in the rating instrument. However, this interpretation is speculative and was not directly tested in the present study; the evaluation instrument did not measure evaluators' perceptions of cultural unfamiliarity, surprise, or uncanniness.

In Boden's (2004) terms, the Full AI condition produced *exploratory novelty* — outputs at the boundary of a known stylistic space — without achieving the deeper *transformational creativity* that characterises expert human innovation. The Full AI outputs were novel *because* they departed from established conventions, not because they demonstrated sophisticated creative problem-solving grounded in domain knowledge.

The implications for design education are significant. If students are evaluated by industry professionals who associate AI-generated deviations with creativity, there is a risk that AI-mediated workflows may displace the development of culturally grounded creative competencies — the knowledge that distinguishes a textile designer from a prompt engineer (Lee, 2024; Öztaş & Arda, 2025).

5.3. Commercial Parity and Educational Implications

The absence of significant differences on Commercial Viability and Technical Feasibility suggests that AI-generated outputs have achieved *market parity* with human-designed alternatives. If commercial and technical equivalence has already been reached, the competitive advantage of human designers must

rest on cultural and contextual dimensions — precisely the criteria on which Full AI underperformed. This reframing has direct implications for textile and fashion curricula: educational priorities should shift toward deepening students' cultural literacy and capacity to evaluate and supervise AI outputs, rather than technical execution skills (Ursu et al., 2024).

5.4. Evaluator Group Differences

The convergence of academic and industry evaluators on Cultural Fidelity is particularly meaningful. Despite differing professional orientations, both groups applied near-identical standards when assessing the preservation of kilim motif integrity, suggesting that cultural fidelity judgements are anchored in shared domain knowledge that is robust across evaluator roles. This makes Cultural Fidelity the most reliable and theoretically grounded criterion in the evaluation instrument.

The higher scores assigned by industry designers on subjective criteria may reflect accommodation to AI aesthetics in commercial contexts (Eisenmann et al., 2026), or genuinely different standards calibrated to contemporary market expectations rather than traditional craft values. Disentangling these interpretations would require follow-up studies measuring evaluators' prior exposure to and attitudes toward AI-generated design.

5.5. Limitations

Several limitations warrant acknowledgement. The student sample (N = 15) was drawn from a single institution; findings may not generalise across educational contexts. The within-subjects design introduces potential order and transfer effects despite counterbalanced evaluation stimuli. Group-mean imputation for two missing designs may slightly attenuate Full AI condition variance. The evaluation rubric has not been independently validated across design domains. Finally, the institutional partnership with MYTH AI, while providing ecological validity, limits generalisability to other platforms with different training data and interface affordances.

6. Conclusion

This study set out to examine whether, and to what degree, human involvement in AI-assisted textile design preserves cultural fidelity. The central finding is clear: human presence functions as a cultural filter that autonomous AI generation cannot replicate through textual instruction alone, and minimal human intervention is sufficient to preserve culturally identifiable characteristics.

At the same time, the study reveals a *creativity–culture trade-off*: the same AI systems that underperform on cultural fidelity produce outputs perceived as more original and creative by expert evaluators. This trade-off suggests that AI adoption in heritage design contexts is not a neutral efficiency gain but a transformation of what counts as creative value — one that carries risks for cultural sustainability if left unmediated by human judgment.

For design educators, the findings offer both reassurance and challenge. Students who engage meaningfully with AI tools — selecting, editing, and ratifying generated outputs — can maintain culturally grounded quality at levels equivalent to fully human production. The challenge is that curricula must explicitly cultivate the cultural literacy and critical design judgment that make this engagement meaningful.

For industry, the commercial parity finding confirms that all three production modes are viable for market-ready outputs. The differentiating factor is cultural depth — a dimension that will determine whether AI-assisted textile design contributes to or erodes the visual heritage of traditions such as the Anatolian kilim.

Future research should extend this work across different cultural traditions, larger and more diverse samples, and longitudinal designs that track how cultural literacy evolves through sustained engagement with AI co-creation tools. The question of *how much human involvement is enough* — and what form it must take — remains among the most pressing questions in human–AI collaborative design education.

Declarations

Competing Interests

The authors declare no financial or personal competing interests related to this study. The study was conducted within the framework of an institutional collaboration protocol between *[University Name]* and MYTH AI. Under this protocol, students were provided with access to the MYTH AI platform through limited-use credits and free usage opportunities, and the use of AI tools in courses was supported during the 2025–2026 academic year. The collaboration also included educational and training activities related to artificial intelligence technologies and prompt engineering. No author received financial compensation, consultancy fees, or other personal financial benefits from MYTH AI in connection with this study. The institutional collaboration did not influence the study design, data collection, analysis, interpretation of the findings, or the decision to submit the manuscript for publication.

Author Contribution

Author 1 conceived and designed the study, developed the experimental protocol and evaluation rubric, collected and analysed the data, and wrote the manuscript.

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Data Availability

The anonymised evaluation dataset (Supplementary File 2), statistical analysis script (Supplementary File 3), blank evaluation rubric (Supplementary File 1), and platform interface documentation (Figures File) are provided as supplementary materials to this submission. A representative sample of the design stimuli used in the evaluation is provided in Figures File "Figure 2 (a), Figure 2 (b), Figure 2 (c)". Full design sets are not publicly available due to the terms of the institutional collaboration agreement with MYTH AI; access to the complete design archive may be requested from the corresponding author, subject to approval by the collaborating organisation.

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Figures

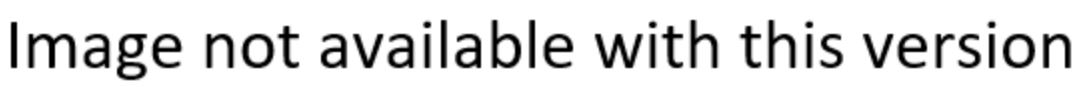


Figure 1

Reference images of the ten traditional Anatolian motifs provided to participants: (1) koçboynuzu, (2) elibelinde, (3) bereket, (4) suyolu, (5) akrep, (6) küpe, (7) yıldız, (8) kurtağzı, (9) pıtrak, (10) çengel.

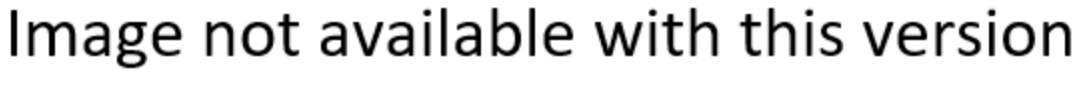


Figure 2

Representative textile designs produced under the three experimental conditions: (a) Human-only, (b) AI-assisted, and (c) Full AI.

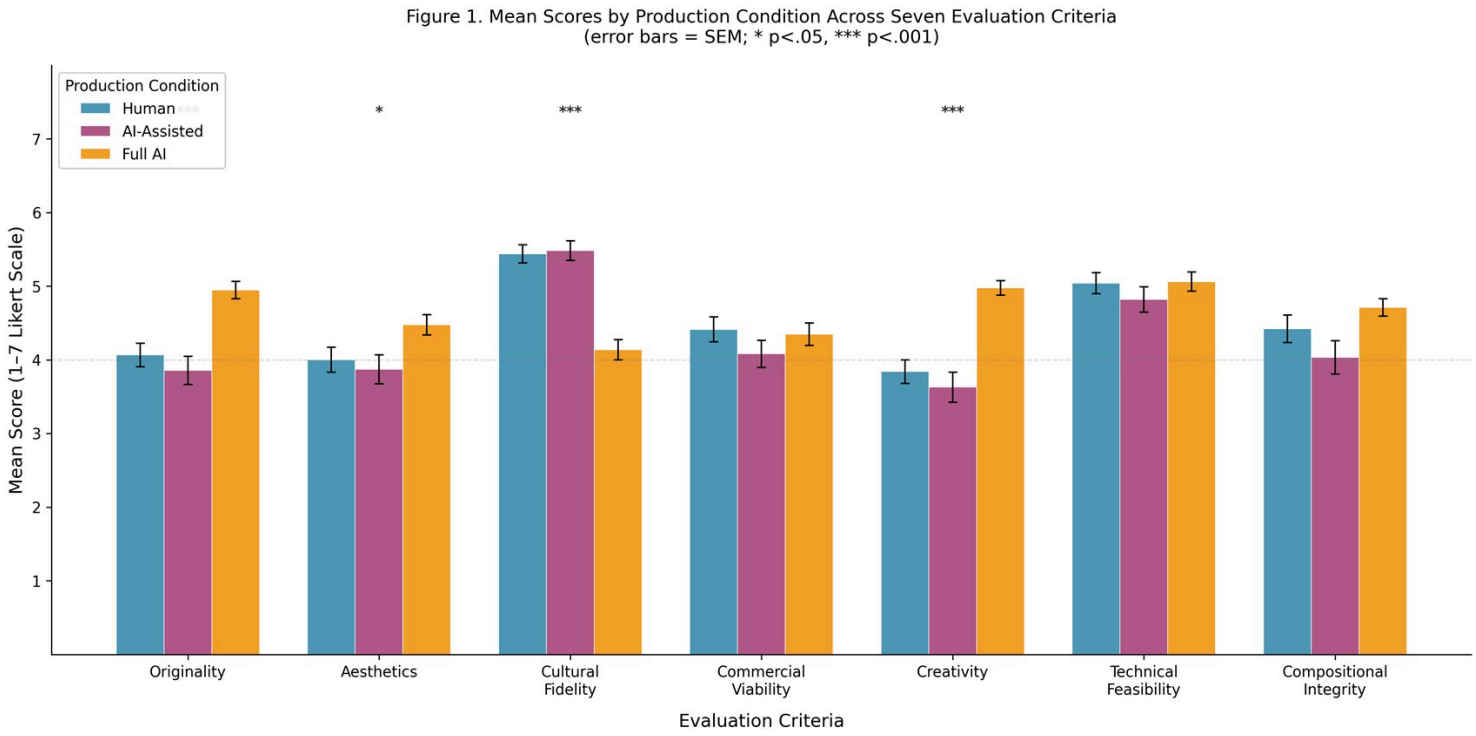


Figure 3

*Mean scores by production condition across seven evaluation criteria (error bars = SEM; * p < .05, *** p < .001).*

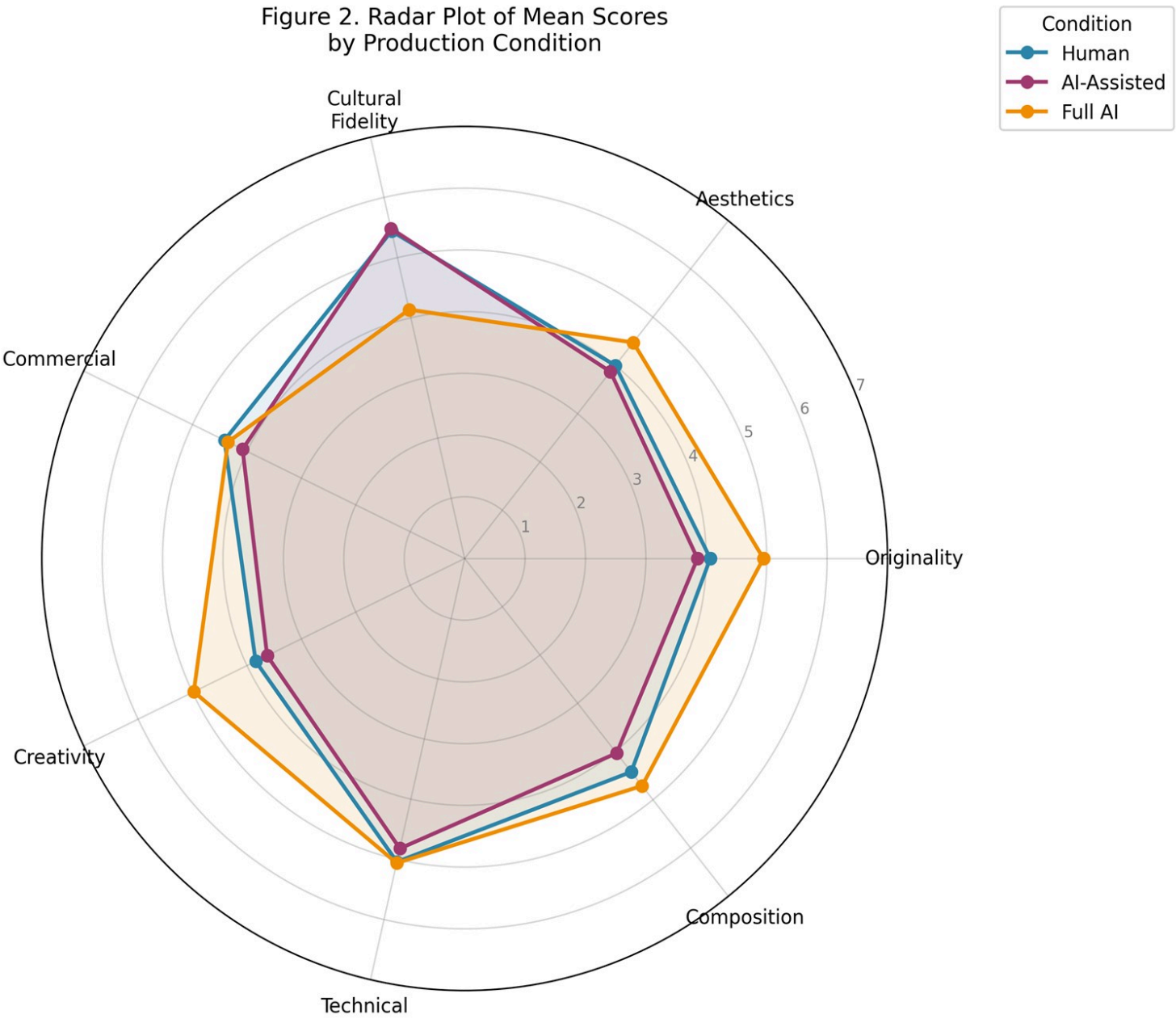


Figure 4

Radar plot of mean scores by production condition across all seven criteria.

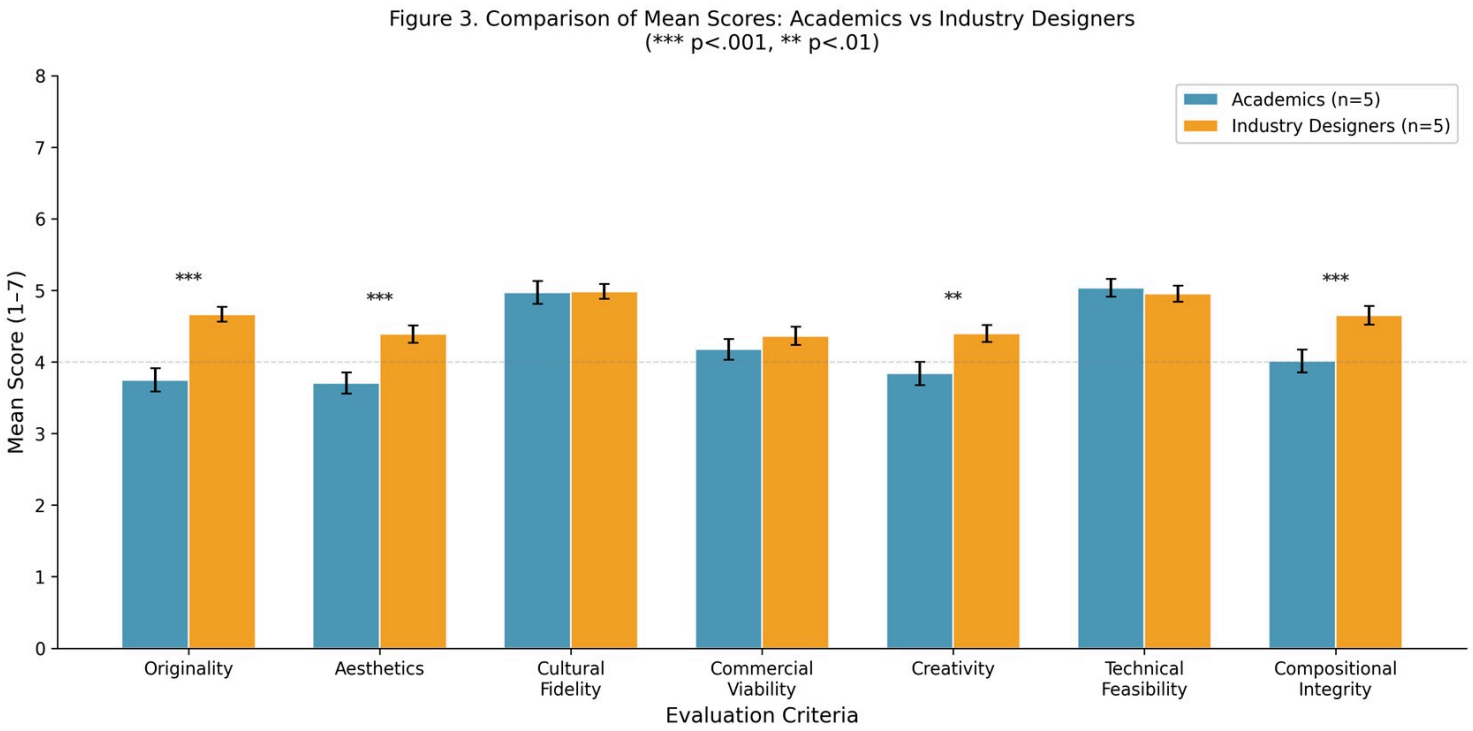


Figure 5

*Comparison of mean scores: Academics vs. industry designers (*** p < .001, ** p < .01).*

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryFile1EvaluationForm1.pdf
- SupplementaryFile2KilimDataAnonymised.xlsx
- SupplementaryFile3Analysisscript.pdf