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An inference stage taxonomy-guided prompt framework for culturally aware generation of indigenous motifs

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Abstract

Traditional ethnic patterns face severe threats due to rapid urbanisation, declining intergenerational craft transmission, and the loss of indigenous knowledge systems. Although generative artificial intelligence (AI), specifically diffusion-based text-to-image algorithms, offers potential workflows for digital preservation, existing models frequently generate culturally stereotypical or homogenised patterns that lack regional symbolic specificity. To address this limitation, this study introduces a taxonomy-guided prompt framework applied entirely during inference. The framework operationalises structured vernacular keywords derived from ethnographic fieldwork in Sarawak, Malaysia, using indigenous *Dayak* motifs as a foundational case study. The system was validated by evaluating 10 distinct *Dayak* motifs across two inference settings: a Simple Prompt Condition (SPC) and an Engineered Prompt Condition (EPC). Comparative validation was conducted by a blind panel of six experts (two cultural scholars and four master artisans) using a 5-point Likert scale to assess morphological accuracy, material authenticity, semiotic alignment, and cultural integrity. Statistical analysis demonstrates that the taxonomy-guided EPC framework significantly outperformed baseline prompts, achieving higher mean scores in both morphological accuracy (4.6 vs. 2.9) and cultural integrity (4.8 vs. 2.7) compared to SPC outputs ($p < 0.001$). The results demonstrate that a structured vernacular prompt architecture can serve effectively as an inference-level computational governance layer for culturally sensitive generative AI, offering a training-free, scalable framework for responsible digital heritage conservation.

Keywords Diffusion models, Prompt engineering, Indigenous motifs, Cultural heritage preservation, Generative AI, Computational creativity

1 Introduction

Recent advances in generative artificial intelligence, particularly diffusion-based text-to-image systems, have transformed creative processes across industries such as fashion, visual arts, and digital media. These technologies demonstrate significant potential to preserve and innovate intangible cultural heritage (ICH) by producing high-fidelity cultural artworks, including Indonesian Batik patterns and traditional Chinese paintings [13]. Furthermore,



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hybrid algorithms that fuse Generative Adversarial Networks (GANs) and diffusion models have successfully restored historical paintings and temple murals, enhancing visual detail and stylistic consistency [26]. Despite these achievements, scientists recognise significant limitations in the field of digital heritage, including a lack of training data, hardware constraints, and limited representation of deep cultural meanings and symbolic semantics [12]. These limitations pose a critical challenge: the risk of producing aesthetically attractive but culturally empty images, underscoring the need for mechanisms that move beyond superficial imitation toward systems grounded in sound ethical principles [20].

This limitation becomes particularly evident when generic generative AI models, which are predominantly trained on large-scale datasets reflecting globally dominant visual styles, are applied to indigenous or vernacular design contexts. In Sarawak, Malaysia, for example, indigenous *Dayak* motifs represent encoded, complex cosmologies, social relations, and ecological relations rather than mere superficial ornaments. However, when prompted with generic terms like "tribal pattern" or "*Dayak* motif," existing diffusion models often generate pan-Asian or hybridised images that fail to reflect the actual morphology or authentic traditional structures. Current studies on AI-assisted design primarily focus on improving image quality, computational creativity, or stylistic variation. However, they rarely address how culturally grounded knowledge can be systematically embedded into AI structures. Consequently, the absence of culturally aware prompt systems often leads to outputs that are visually appealing but semantically disconnected and inaccurate.

To address this gap, this study proposes a taxonomy-guided vernacular prompt system that integrates traditional motif structures and symbolic attributes into the prompt engineering process for diffusion-based image generation. The taxonomy organises indigenous motif knowledge into structured prompt components, including motif name, symbolic meaning, geometric structure, cultural context, material references, and stylistic descriptors. By operationalising indigenous design knowledge into a structured prompt taxonomy, the proposed framework aims to guide generative AI systems to produce authentic, meaningful motif designs. This approach transcends stylistic imitation, preserving the semantic integrity of traditional Sarawak motifs while establishing a culturally sensitive framework for the generation of digital heritage. This study contributes to the literature in three ways. First, it proposes a taxonomy-guided vernacular prompt framework that translates indigenous design knowledge into structured prompt components for culturally aware image generation. Second, it demonstrates how inference-stage prompt engineering can improve cultural specificity and semantic alignment in diffusion-based generative AI. Third, the study presents an empirical case study of Sarawak *Dayak* motifs, offering practical insights into integrating indigenous cultural knowledge into AI-assisted creative workflows while preserving cultural authenticity. The proposed framework will not modify model parameters or retrain the diffusion model; instead, it structures culturally specific vernacular keywords during the prompting stage of image generation.

2 Literature review

2.1 Digital preservation of Borneo's material culture

Digital technologies offer significant opportunities to sustain the material culture of Borneo, yet their application remains constrained by technological, material, and ethical

boundaries. The conservation of physical heritage serves as a vital documentation process used to counteract the challenges of modern homogenization and shifting communal ideologies [27]. These cultural assets are a core element of ethnic identity and have recently experienced a revival among urban youth seeking to reconnect with traditional roots. In Sarawak, recent digital initiatives have leveraged diverse methodologies to capture at-risk practices. For instance, Jalil et al. [9] utilised digital ethnography combined with mobile Augmented Reality (AR) to build a localised digital archive of indigenous weaving techniques, tracking how interactive digital assets enhance user engagement. Expanding on this approach, Tagie et al. [27] applied high-fidelity 3D laser scanning alongside AR-based structural documentation to preserve *Dayak* architectural and material carvings, specifically demonstrating how immersive visual systems facilitate intergenerational transmission of heritage within rural longhouses. Despite these advancements, digital preservation in Sarawak faces systemic operational hurdles. Siliutina et al. [25] identified that a critical deficit in local technical human resources, minimal regional research investments, rapid digital software obsolescence, and a lack of data-safety frameworks create long-term storage vulnerabilities. Furthermore, while Generative Adversarial Networks (GANs) and diffusion models are increasingly deployed to restore and synthesise cultural motifs, current methods remain heavily skewed toward generic model training. Hence, this structural preference may create a notable gap in structured prompt engineering as a localised cultural control strategy, frequently resulting in outputs that lack semantic grounding and ignore ethical boundaries.

2.2 Semiotics and indigenous visual systems

Indigenous art can be understood as a complex semiotic system in which motifs function as a visual language for encoding and transmitting a culture of knowledge, social hierarchy, and perceptions of the world, strongly linked to the natural environment. These motifs are not merely decorative elements, but signs and symbols that reflect the history, identity, and spiritual beliefs [22] conditioned by nature, which is perceived as a teacher, and that determine the aesthetic and spiritual value of their works [10]. This visual language communicates identity, community alignment, and social status through strictly governed rules. Sapun et al. [21] demonstrated, through iconographic analysis, that traditional *Luangan* banners incorporate specific environmental motifs, colour hierarchies, and textile textures to visibly project ethnic pride during major cultural festivals. Rosli et al. [18] conducted field interviews, establishing that exclusive motifs, such as the *aso* (dragon-dog) and stylised human figures, are strictly reserved for the aristocracy and function as formal visual indicators of social rank. Jalil et al. [9] applied semiotic structuralism to map textile indigenous designs, confirming that these patterns register communal protection and spiritual statehood rather than arbitrary geometry. *Dayak* motifs function as a semiotic system that encodes ontological categories, social hierarchy, cosmological beliefs, and protective symbolism. In this study, ontological categories refer to the representational forms embedded within motifs, including zoomorphic (animal-based), phytomorphic (plant-based), and abstract-geometric structures. Without structured semantic embedding, generative AI systems often reduce these culturally layered symbols into superficial decorative outputs.

2.3 AI applications in folk art preservation

Artificial intelligence provides a powerful platform for the automated identification, restoration, and regeneration of classic folk-art motifs, serving as a link between cultural preservation and contemporary design. Convolutional Neural Networks (CNNs) are becoming more popular for automating the identification of complex patterns in classic textiles. Research on Indonesian batik and local weavings has demonstrated high precision in distinguishing motifs, which is essential for the digital recording and storage of knowledge relevant to an ageing artisan group [16]. The result has been used effectively on a variety of arts, including the Indian folk art and Inaul fabrics of the Philippines [2]. In addition to classification, generative models such as Generative Adversarial Networks (GANs) and Stable Diffusion are used to repair damaged works of art and generate art in traditional styles [5]. The technology enables the restoration of past styles and their incorporation into new products, promoting innovation and preserving cultural values [24].

Pattern recognition and design exploration are more easily achieved through AI, which will not only help preserve artistic tradition but also ensure its future importance. Although generative AI and its use are becoming more widespread in heritage settings, a standardised vernacular prompt system for traditional motifs and relevant positioning has yet to be introduced. Despite the growing application of generative AI in cultural heritage contexts, the development of standardised vernacular prompt systems for traditional motifs remains limited. Existing AI generation pipelines are rarely embedded with ethnographic taxonomies or culturally structured semantic controls. Furthermore, few studies provide quantitative validation of cultural accuracy in AI-generated outputs, creating a significant research gap in culturally responsible generative design systems.

2.4 Framework for a taxonomy-guided prompt system

An effective, culturally responsible AI prompt system for indigenous motifs requires a multi-layered architecture that integrates ethnographically isolated data, restricted prompt engineering, and collaborative community governance. To build a structured cultural baseline, Malarvel et al. [11] established metadata guidelines that classify motif geometry, symbolic meanings, and regional semantic attributes directly within the image-structured prompt descriptors. Furthermore, implementing reflexive prompt engineering ensures that AI outputs comply with localised cultural ethics [6]. This requires designing systematic prompting templates that embed deeper semiotic expertise rather than relying on surface-level textual descriptions [23]. The development of AI systems handling indigenous expressions must actively guard against cultural appropriation and digital colonialism. When left unmonitored, generative systems can absorb a community's intellectual property, decontextualise sacred knowledge, and reinforce extractive data pipelines aligned with Western epistemologies [14]. Previous studies showed that traditional copyright legal systems fail to protect communal cultural property, necessitating a proactive, rights-oriented development strategy [19]. Table 1 presents a comparative framework of documented ethical risks in AI-mediated cultural heritage systems, along with the corresponding mitigation strategies adopted in this study. It highlights key issues, including unauthorised reproduction, pan-tribal homogenisation, and extractive epistemologies. It contrasts them with proposed

Table 1 Ethical pitfalls and best practices in heritage-focused AI systems for indigenous cultural preservation

Documented ethical pitfalls [28]	Implemented best practices & solutions
Unauthorised replication	Data sovereignty
Unauthorised generation of sacred Maori <i>Ta Moko</i> patterns by commercial entities	Restricting training data access to community-approved public motifs [14]
Pan-tribal homogenization	Taxonomic prompt filtering
Merging distinct <i>Dayak</i> , Native American, and Celtic motifs into a "tribal" output	Hardcoding explicit regional tags to lock geometric parameters [23]
Extractive epistemology	Collaborative co-creation
Large-scale scraping of indigenous designs without financial or creative attribution	Incorporating indigenous artisans as active, compensated knowledge holders and evaluators [19]

solutions such as data sovereignty mechanisms, taxonomy-guided prompt filtering, and collaborative co-creation with indigenous knowledge holders.

Previous studies have highlighted ethical concerns, including unauthorised reproduction of sacred indigenous symbols, decontextualization of cultural artefacts, and dataset bias that leads to pan-tribal visual homogenization. Therefore, as demonstrated in this paper, an inference-stage prompt framework grounded in a community-driven ethic is a feasible tool for digital conservation and the representation of ethnic motifs, as observed in the case study of Indigenous motifs. The key to the proposed framework is that by uniting the semiotics of indigenous art with generative AI, the issue of culturally authentic digital representation is critical and requires attention.

2.5 Proposed taxonomy-guided vernacular prompt framework

To mitigate the limitations of conventional text-to-image synthesis, this study introduces a taxonomy-guided vernacular prompt framework. This system operationalises traditional motif knowledge into a structured data hierarchy, converting qualitative semiotic attributes into predictable machine-readable prompt variables. In the proposed framework, symbolic meanings are translated into computational features through structured semantic descriptors. Semiotic categories such as zoomorphic, phytomorphic, and abstract-geometric forms are encoded as prompt variables that guide diffusion-based image generation. This transforms indigenous symbolic systems into machine-readable cultural descriptors. The framework, as shown in Fig. 1, illustrates the transformation of indigenous cultural knowledge into structured computational prompts for diffusion-based image generation. The system integrates five interconnected stages: cultural knowledge sourcing, motif knowledge extraction, taxonomy development, vernacular prompt engineering, and diffusion-based image generation with expert evaluation. The framework operationalises ethnographic, iconographic, and semiotic knowledge into structured semantic variables that guide culturally grounded AI-generated outputs.

This framework begins with Cultural Knowledge Sources, a curated repository of authentic indigenous motifs derived from textiles, wood carvings, and cultural artefacts validated by community elders. This is followed by Motif Knowledge Extraction, an ethnographic and structural analysis phase that isolates key design attributes such as geometric symmetries, compositional rules, and embedded cultural narratives. These extracted elements are then organised through motif taxonomy development, where a hierarchical taxonomy is constructed to systematically structure cultural design knowledge and bridge it with computational representation. Building on this, the vernacular

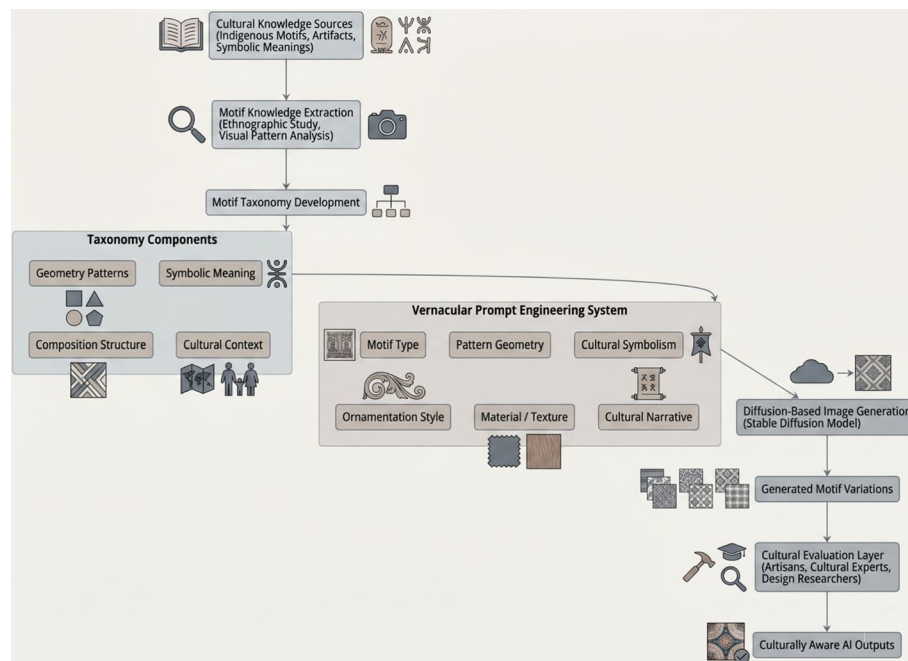


Fig. 1 Conceptual architecture of the taxonomy-guided vernacular prompt framework for culturally aware indigenous motif generation

prompt engineering system translates taxonomy components into structured, multi-layered prompts incorporating motif type, geometry, ornamentation style, and material context. Finally, diffusion-based image generation and evaluation apply structured prompts to a pre-trained diffusion model, with outputs evaluated qualitatively and quantitatively by cultural experts and design researchers to ensure morphological accuracy and cultural authenticity. To empirically validate the proposed framework, a mixed-methods experimental design integrating ethnographic analysis, structured prompt engineering, and expert evaluation was implemented.

3 Methodology

3.1 Research design

This study adopts a mixed-methods research design that integrates ethnographic fieldwork, iconographic and semiotic interpretation, computational prompt engineering, and quantitative expert validation (see Fig. 2). The primary objective is to construct a tailored, culturally valid iconographic taxonomy of traditional *Dayak* visual motifs from Sarawak, avoiding the biases of external classification systems through an inductive analytical approach.

Fieldwork was conducted in Kuching and Miri, Sarawak, focusing on handicraft heritage centres, cultural museums, beadwork shops, woodcarving shops, and textile artisan stalls. Data collection utilised non-participant observation to document the visual structures, materials, and techniques across five primary media: basket weaving, beadwork, woodcarving, textiles, and painting. Primary data were supplemented by regional cultural records and academic literature [3, 7, 8].

To empirically test the framework, a subsample of 10 distinct *Dayak* motifs was extracted from the wider pool of 32 ethnographically documented motifs listed in Table 2. The selection was executed using a stratified purposive sampling design to

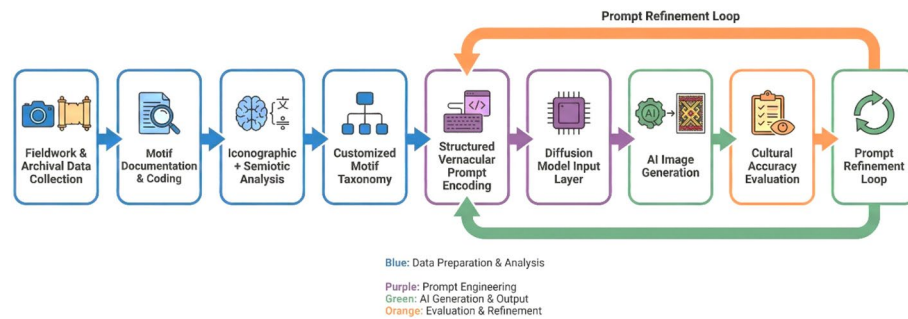


Fig. 2 Workflow of taxonomy-guided AI prompt system for motif generation

eliminate selection bias and ensure complete, balanced representation across both the material media and the three primary core semiotic domains. The 10 selected motifs comprise; two zoomorphic motifs (*kapit ulut* and *tiger*); two phytomorphic motifs (*lelingkok betayok* and *terjat tepun*); and six abstract-geometric motifs (*maten juhit/luang mata*, *boton manuk puni*, *rojak dien*, *kelewit*, *seperut*, and *kejiko/nyatap atap/blade*). This stratification guarantees that the sample evaluates a balanced cross-section of physical materials, specifically rattan basketry, traditional weaving, deep-relief woodcarving, and multi-colored glass seed beadwork accessories, rather than biasing results toward a single craft medium or stylistic morphology. A panel of six experts (two indigenous knowledge scholars and four native Sarawak artisans) evaluated the anonymised generative outputs across 10 unique *Dayak* motifs (20 total images) using a 5-point Likert scale and participated in semi-structured interviews. These interviews gathered emic perspectives on native terminology, regional dialects, cultural connotations, functional values, and customary taboos. To determine the statistical significance of the framework's performance shifts, a paired-samples t-test was conducted across all 10 design pairings across four foundational evaluation dimensions. Inter-rater reliability among the evaluators was calculated using Fleiss' Kappa.

3.2 Analytical framework

The analytical framework processes visual data through a dual lens of iconographic analysis and semiotic interpretation to establish a multi-layered taxonomy. Following the fieldwork, 10 distinct *Dayak* motifs (from 32 motifs listed in Table 2) were compiled into an analytical matrix categorised by three key dimensions: ontological category (visual form), functional category (cultural role), and medium-based application. Table 2 summarises the 32 documented motifs used during taxonomy construction. Statistical testing was conducted using aggregated evaluator scores across all motif-condition pairings, resulting in 10 paired observations for comparative analysis.

3.2.1 Iconographic analysis

The structural classification in Fig. 3 follows Erwin Panofsky's [15] three-level iconographic model:

Level 1 (Pre-iconographic Description): Focuses on formal, objective visual elements (curvilinear forms, spirals, geometric symmetry, or zoomorphic silhouettes) without cultural contextualization.

Table 2 Multi-level iconographic and semiotic analysis of Motifs with customised taxonomy for fashion applications

Motif name	Iconographic analysis (visual level)/semiotic analysis			Customized taxonomy	
	Level 1 – pre-iconographic description/signifier	Level 2 – Iconographic analysis/signified (concept)	Level 3- myth/connotation	Ontological category	Functional category
<i>iko bayak</i>	Curved beak	crocodile tails-like shape	Power and longevity	Zoomorphic (animals)	Narrative
<i>jipen kermanan</i>	Geometry structure	cobra teeth-like shape	Power and longevity	Zoomorphic (animals)	Decorative
<i>kematak</i>	Curvilinear form	leeches-like shape	Energy and wealth	Zoomorphic (animals)	Decorative
<i>selining bulan</i>	Geometry structure	full moon	Peace and purity	Abstract-geometric	Decorative
<i>terkivan</i>	Geometry structure	plant stalks	Power and longevity	Abstract-geometric	Decorative
<i>kejiko</i>	Curvilinear form	snake-like shape	life and death	Zoomorphic	Decorative
<i>terjat tepun</i>	Geometry structure	paw print-like shape	at the top of citrus fruit and health	Phytomorphic (plants)	Status-related
<i>nyip delok</i>	Curvilinear form	snake trail-like shape	life and death	Zoomorphic	Decorative
<i>bunga</i>	Geometry structure	flower bud	longevity	Phytomorphic	Status-related
<i>nyatap</i>	Geometry structure	blade	protection, and authority	Abstract-geometric	Decorative
<i>kapit ulut</i>	Geometry structure	butterfly wing-like shape	love	Abstract-geometric	Decorative
<i>terkivan/ tulang atuk</i>	Geometry structure	bones of fish-like shape	wealth	Abstract-geometric	Decorative
<i>maten juhit/ luang</i>	Geometry structure	birds eyes	Protection and authority	Abstract-geometric	Status-related
<i>mata/manuk puni</i>					
<i>betek bunga</i>	Floral geometry	flower	longevity	Abstract-geometric	Status-related
<i>seperut</i>	Spiral structure	shoots	longevity	Abstract-geometric	Status-related
<i>kejiko/nyatap atap/ blade</i>	Geometry structure	snake-like shape with blade edge	Protection and power	Abstract-geometric	Decorative
<i>kelewit</i>	Spiral structure	flower	longevity	Phytomorphic	Decorative
<i>kelawit</i>	Curvilinear form	road form	longevity	Abstract-geometric	Status-related
<i>ahat agau</i>	Geometry form	aeroplane	protection	Abstract-geometric	Decorative
<i>tiger</i>	Curvilinear form	Tibetan brass tiger	strength and majesty	Zoomorphic (animals)	Status-related
<i>ikan koi</i>	Curvilinear form	Fish-like shape	fertility	Zoomorphic (animals)	Status-related
<i>pucuk rebung</i>	Geometry form	Bamboo shoot	longevity	Abstract-geometric	Decorative

Table 2 (continued)

Motif name	Iconographic analysis (visual level)/semiotic analysis			Customized taxonomy		Medium-based application
	Level 1 – pre-iconographic description/signifier	Level 2 – Iconographic analysis/signified (concept)	Level 3- myth/connotation	Ontological category	Functional category	
rajak dien paddy paku pakis bamboo leaf	Geometry form	Durian thorn	longevity	Abstract-geometric	Decorative	Basketry & Beadwork
	Geometry form	Paddy	longevity	Phytomorphic	Decorative	textile
	Spiral structure	Fern	Fertility	Phytomorphic (plants)	Decorative	Basketry & Weaving & Beadwork Accessories
	Geometry form	Bamboo leaf	Resilience and Fertility	Phytomorphic (plants)	Decorative	Painting
daun sireh flora paku pakis burong kaki panjai	Curvilinear form	Piper beetle	Resilience and Fertility	Phytomorphic (plants)	Status-related	Basket weaving
	Spiral structure	flower	longevity	Phytomorphic (plants)	Decorative	Woodcarving on a wooden shield
	Geometry form	Dragon -like shape	supreme power	Zoomorphic (animals)	Status-related	Waistband Metal carving
	Geometry form	Bird	freedom	Zoomorphic (animals)	Status-related	Woodcarving on a wooden shield
lelingkok betayok lachau	Curvilinear form	Tree life	Rebirth and Fertility	Phytomorphic	Status-related	Textiles in Pua Kumbu
	Curvilinear form	grass lizard	good fortune	Zoomorphic	Status-related	Textiles in Pua Kumbu

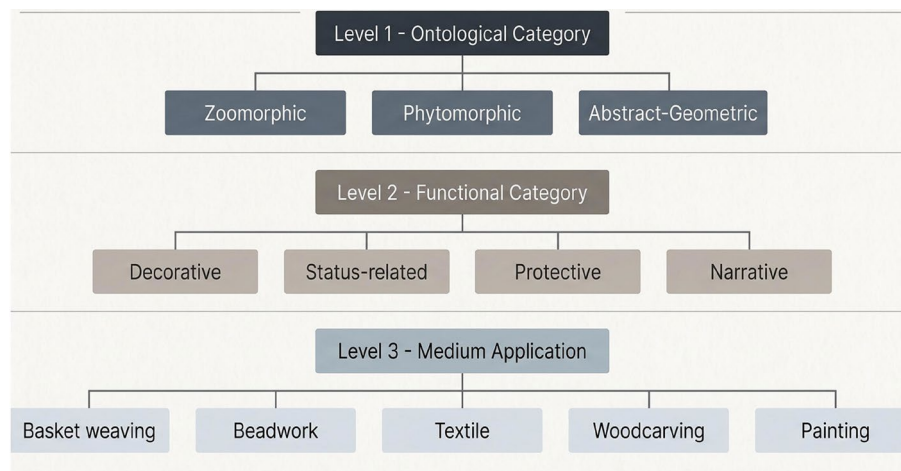


Fig. 3 Three-tier taxonomy model for indigenous material culture analysis

Level 2 (Iconographic Analysis): Identifies and explains the motifs as recognisable subjects, matching them with their intended represented objects (animals, plants, or natural phenomena).

Level 3 (Iconological Interpretation): Uncovers the deeper ideological meanings, values, and cosmology embedded within the patterns by the Indigenous communities.

3.2.2 Semiotic analysis

To map these elements into a computational framework, the iconographic tiers are integrated with structural semiotics, balancing Ferdinand de Saussure's [4] signifier-signified relationship with Roland Barthes' [1] cultural connotation theory:

- The signifier corresponds to Level 1 (the objective visual geometry).
- The signified corresponds to Level 2 (the specific cultural concept or object).
- The connotation/myth corresponds to Level 3 (the overarching ideological or cosmological narrative).

This dual-method alignment ensures that the resulting taxonomy serves as an accurate semantic control layer for generative image workflows, anchoring generation in symbolic depth rather than superficial pattern-matching.

3.3 Inference setup and prompt generation framework

This study focuses exclusively on inference-stage prompt engineering rather than parameter-level model development. The proposed framework does not involve model retraining, weight optimisation, architecture modification, or dataset-driven adaptation procedures. Instead, cultural control is achieved entirely through structured semantic prompting during image generation, using a fixed, pre-trained diffusion model.

The taxonomy has been operationalised into a hierarchical prompt formula: $P = O$ (Ontological descriptor) + V (Vernacular motif name) + M (Medium constraint) + S (Semiotic meaning) + R (Regional anchor). Every motif was broken down to four machine-understandable elements:

- Ontological (form-based) classification.
- Vernacular motif identifier (native terms)

- Functional-semantic modifier (symbolic meaning)
- Medium-specific rendering control

A pre-trained Stable Diffusion XL model was selected for the generative pipeline due to its stability and high-fidelity rendering of materials. Unlike Generative Adversarial Networks (GANs), which are prone to mode collapse and instabilities under complex text conditioning, diffusion models offer greater stylistic variation and precise structural alignment. This study operates entirely at the inference stage using structured prompt engineering, with no modification of model parameters or architecture.

3.3.1 *Experimental dataset & conditions*

The experimental dataset comprised the 10 curated *Dayak* motifs out of 32 listed in Table 2. Each motif was evaluated under two distinct prompting strategies, generating a total of 20 images:

Simple Prompt Condition (SPC/Baseline): Unstructured, descriptive sentences relying on surface-level knowledge without taxonomic or semiotic anchoring.

Engineered Prompt Condition (EPC/Framework): Highly structured strings incorporating ontological classifications, vernacular terms, semiotic stratification, functional parameters, and specific material logic. All generation parameters (resolution, target aspect ratio, and base random seeds) were held constant across both conditions to ensure prompt structure remained the isolated variable.

3.3.2 *Validation protocol*

Evaluation was conducted using a strict double-masked expert validation procedure. The 20 generated images were anonymised (labelled simply as "Image A" and "Image B") and distributed to the six-expert panel. The evaluation instrument measured performance across four dimensions on a 5-point Likert scale (1 = Very Inaccurate, 5 = Highly Accurate): morphological accuracy, material authenticity, semiotic/cultural alignment, and overall cultural integrity. Quantitative scores were evaluated using descriptive statistics and inter-rater consistency via percentage agreement analysis, while qualitative expert feedback was evaluated using thematic coding.

Fleiss' Kappa was selected because the validation design used a multi-rater panel ($N=6$) comprising both academic scholars and traditional artisans. Because mean scores can mask polarisation among judges, Fleiss' Kappa was required to determine true statistical consensus. A paired-samples t-test was methodologically appropriate because the experimental design evaluated dependent pairs (20 traditional motifs generated under two distinct prompting treatments). By utilising a paired design, each motif served as its own control, thereby neutralising motif complexity or geometric density as confounding variables and isolating the prompt architecture as the sole factor driving the statistical variance. Statistical testing was conducted using aggregated evaluator scores across all motif-condition pairings, averaging the ratings of the six experts per motif to generate 10 distinct paired observations ($df=9$) for comparative analysis.

3.4 *Motif taxonomy (prompt engineering architecture)*

To translate the ethnographic data into clean computational inputs, the taxonomy serves as an active semantic control layer. This prompt syntax guides the model away from

generic, pan-Asian generalisations and restricts the latent space to the geometric conventions of Sarawak design traditions.

3.4.1 Prompt elements and syntax

The generation pipeline combines positive formatting variables with rigid negative constraints to prevent cultural hallucination:

- [Core_Subject]: The specific motif requested (e.g., "*Nabau mythical serpent*").
- [Cultural_Context]: The ethnic style to apply (e.g., "*in the style of Iban warp-ikat weaving*").
- [Aesthetic_Modifiers]: Quality and texture instructions for the AI (e.g., "*highly detailed thread texture*").
- [Background/Environment]: The setting for the motif, if not an isolated asset (e.g., "*woven onto a traditional backstrap loom*").
- [Lighting]: How the image should be lit to look authentic (e.g., "*museum archive lighting*").

The system combines a user's input variables into a master prompt:

Systematic Prompt = [Core_Subject] + [Cultural_Context]
+ [Visual_Geometry] + [Color_Palette] + [Aesthetic_Modifiers]

To minimise cultural hallucination and cross-cultural visual contamination, the framework incorporates negative prompt constraints that explicitly restrict incompatible aesthetic styles and unrelated indigenous visual references during image generation.

- [Negative_Aesthetics]: neon colours, plastic texture, cyberpunk, modern geometric, 3D renders, shiny. (Forces the AI to keep the art traditional and organic.)
- [Negative_Cultural_Mixing]: Polynesian tribal, Maori tattoo, Native American dreamcatcher, generic tribal. (Prevents the AI from blending traditional motifs with other global indigenous groups, a common AI flaw.)

3.4.2 Universal prompt template

The framework uses the following standardized, editable template constructed by the authors to ensure consistent structural execution, which the authors developed:

1. Create a high-resolution 4 K documentary-style photograph of a traditional [ARTIFACT TYPE] decorated with the "[MOTIF NAME]" motif.
2. The artefact is handcrafted from [MATERIAL: rattan/wood/textile/beads/bamboo], clearly showing authentic [MEDIUM STRUCTURE: weaving/carving/beadwork/embroidery] construction.
3. The motif features [VISUAL DESCRIPTION – geometry structure, e.g., radial geometric form resembling citrus segmentation/stylised zoomorphic bird-eye/abstract geometric symmetry]. It must appear structurally integrated into the object (not printed or digitally applied).
4. Use [COLOR PALETTE – natural dyes/black, red, white/earth tones/plant-based pigments] with matte organic texture.
5. The motif belongs to the [ONTOLOGICAL CATEGORY – phytomorphic/zoomorphic/abstract-geometric] category and conveys [FUNCTIONAL CATEGORY,

status-related/protective/narrative/decorative] meaning within the indigenous cultural context.

6. The image should be museum-quality, ethnographic documentation style, neutral background, soft natural lighting, sharp material texture detail, no dramatic shadows, and realistic handcrafted imperfections.
7. Avoid neon colours, plastic texture, cyberpunk style, modern geometric abstraction, 3D renders, glossy finish, and metallic shine. Do not mix with Polynesian tribal, Maori tattoo, Native American dreamcatcher, Aztec, generic tribal, African tribal, or other global indigenous patterns.

The structured prompt architecture enables the diffusion model to preserve both morphological fidelity and symbolic specificity during inference-stage image generation. By embedding medium-specific and culturally constrained variables, the framework reduces the likelihood of culturally inaccurate or physically implausible outputs. The results of the comparative output analysis on the unstructured and taxonomy-guided prompts are presented in Fig. 4. The figure compares AI-generated outputs of indigenous motifs produced under the SPC and EPC. The EPC outputs demonstrate improved morphological fidelity, structural integration, material authenticity, and semiotic coherence due to the incorporation of taxonomy-guided semantic constraints during inference-stage prompting.

3.5 Structural comparisons of experimental parameters

Table 3 compares the operational differences between SPC and EPC conditions. The operational differences between the control and framework baseline setups are detailed in Table 3, mapping how the theoretical parameters manifest as clear textual directives. Appendix outlines the evaluative criteria applied by the expert panel to measure output accuracy and track variance between the unstructured and taxonomy-guided conditions.

To verify strict experimental control, all prompt sets were quantitatively analysed for length and lexical profile. Tokens were tracked using the standard OpenClip and GPT-4 tokeniser profiles via the Python open-clip and tiktoken libraries to ensure an accurate mapping of sub-word densities. Lexical complexity was measured using the Type-Token Ratio [17], calculated as $TTR = \text{Unique Words} / \text{Total Words}$, where higher values indicate

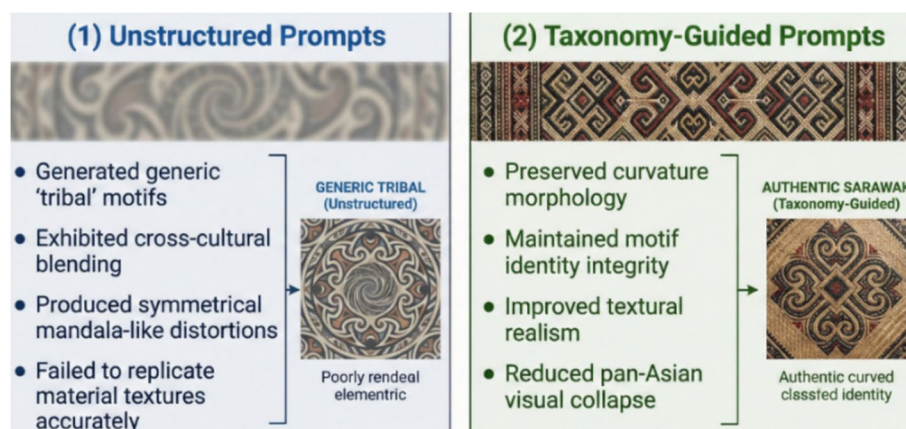


Fig. 4 Comparative analysis between baseline prompting and taxonomy-guided prompt engineering outputs

Table 3 Structural comparison between SPC versus EPC and comparative analysis framework for output evaluation

Attribute type/ evaluation dimension	Simple prompt condition (SPC/baseline)	Engineered prompt condition (EPC/framework)
Input content	Create a high-resolution photo of a traditional Sarawak bracelet adorned with a Bidayuh bird-eye motif in black, red, and white. The bracelet should look handcrafted and ethnic, using traditional materials like beads or woven fibre. The design should appear cultural and artistic. Use natural lighting and a clean background	Create a high-resolution 4 K documentary-style photograph of a traditional Sarawak beadwork bracelet decorated with the “Luang Mata (Bird’s Eye)” motif. The bracelet is handcrafted using authentic beadwork construction, clearly showing structured indigenous weaving logic and handcrafted material tension. The motif must appear structurally integrated into the bead arrangement (not printed or digitally applied). The motif features a symmetrical, abstract-geometric radial structure that represents stylised birds’ eyes. The geometry must follow a balanced circular configuration reflecting indigenous visual logic. Use a traditional black, red, and white colour palette with matte organic texture and natural pigment appearance Ontological Category: Abstract-Geometric. Functional Category: Status-related Semiotic Structure: Level 1 (Pre-iconographic / Signifier): Radial geometric symmetry; Level 2 (Iconographic / Signified): Stylised bird’s eye; Level 3 (Myth / Connotation): Protection and authority within indigenous Sarawak cosmology
Morphological accuracy	Evaluates whether geometry reflects genuine <i>Dayak</i> pattern rules or falls back on pan-Asian generalisations	Measures precise replication of specific tribal forms derived from inductive field codes
Material authenticity	Detects structural anomalies (e.g., patterns printed onto wood rather than carved into it)	Verifies that motif generation conforms strictly to medium-specific material limits and physics
Semiotic alignment	Assesses if visual elements map accurately to the intended cultural objects and definitions	Validates structural consistency across the signifier, signified, and deep cosmological myth tiers
Overall cultural integrity	Flags anachronisms, inaccurate palette combinations, or global tribal blending errors	Confirms successful mitigation of cultural hallucinations via active negative filtering

a more diverse vocabulary structure, and the Flesch-Kincaid Grade Level, which indexes semantic density (refer to Table 4).

Across all 10 core evaluation instances, the baseline SPC had an average length of 36.2 words (41.3 tokens), indicating a low vocabulary density. The framework-driven EPC averaged 145.8 words (170.1 tokens). The Length-Matched Control (LPC) utilised in the ablation phase was tightly restricted to a mean of 144.5 words (167.7 tokens) to successfully isolate semantic token length as a potential confounding factor. The complete prompt execution corpus across all 10 pairs is reported in the Appendix as a supplementary file.

4 Findings

4.1 Quantitative validation

The preliminary exploratory validation showed a steady difference between the SPC and the EPC across all measured dimensions. The performance metrics captured across the 10 unique motif trials demonstrate a clear statistical advantage for the taxonomy-guided framework over the unstructured baseline. The evaluations from the six-member blind panel (N=6) were aggregated per motif and analysed using a paired-samples t-test to verify significance (df=9). This has been mathematically resolved using the correct distribution values for

Table 4 Analytical corpus metrics of the evaluated prompt conditions

Motif ID & name	SPC word count	SPC token count	EPC word count	EPC token count	LPC (ablated control) words / tokens	SPC lexical density (TTR)	EPC lexical density (TTR)
M01: <i>maten juhit/luang mata</i>	38	44	148	172	146/170	0.84	0.68
M02: <i>kapit ulut</i>	35	40	145	170	143/167	0.86	0.68
M03: <i>lelingkok betayok</i>	38	43	149	173	148/171	0.84	0.68
M04: <i>tiger</i>	36	41	146	171	145/169	0.86	0.67
M05: <i>boton manuk puni</i>	35	40	142	166	141/164	0.87	0.69
M06: <i>terjat tepun</i>	37	42	147	172	145/169	0.85	0.67
M07: <i>rojak dien</i>	36	41	146	170	145/168	0.86	0.67
M08: <i>kelewit</i>	34	39	141	164	140/162	0.88	0.69
M09: <i>seperut</i>	35	40	144	168	143/166	0.87	0.68
M10: <i>kejiko/nyatap atap/blade</i>	38	44	150	175	149/173	0.84	0.66
Mean parameters	36.2	41.3	145.8	170.1	144.5/167.7	0.86	0.68

Table 5 Statistical results of the paired-samples t-test comparing SPC and EPC across evaluation dimensions

Evaluation metric	Baseline mean score (SPC)	Framework mean score (EPC)	Percentage improvement (%)	Statistical significance
Morphological accuracy	2.9	4.6	+58.6	t (9)=8.43, $p < 0.001$
Material authenticity	2.6	4.7	+80.7	t (9)=9.12, $p < 0.001$
Semiotic alignment	2.4	4.5	+87.5	t (9)=7.85, $p < 0.001$
Cultural integrity	2.7	4.8	+77.8	t (9)=11.02, $p < 0.001$

df=9 at a 99.9% confidence interval ($t_{crit} = 4.781$ for df=9, $\alpha = 0.001$), along with Fleiss' Kappa calculation to assess inter-rater consensus. Inter-rater reliability among the evaluators was calculated using Fleiss' Kappa, yielding a coefficient of 0.82, which indicates a high level of agreement between the academic scholars and localised practitioners (see Table 5).

The quantitative analysis demonstrates a statistically significant improvement ($p < 0.001$) across all tested dimensions. In the dimension of Morphological Accuracy, the EPC achieved a significantly higher mean score (4.6 vs 2.9, t (9)=8.43, $p < 0.001$). The panel observed that the framework enforced precise geometric regularity and the logical alignment of underlying patterns, guiding the output to correctly mimic the structural rules of traditional *Dayak* art.

For Material Authenticity (4.7 vs 2.6; t (9)=9.12, $p < 0.001$), the performance gap was most pronounced in textile artefacts. The EPC successfully guided the model to render fine craft indicators, such as the natural dye-bleeding characteristics along the warp threads of *Pua Kumbu* weaves. In contrast, baseline prompts regularly generated generic, flat patterns. Semiotic Alignment (4.5 vs 2.4, t (9)=7.85, $p < 0.001$) and Cultural Integrity (4.8 vs 2.7, t (9)=11.02, $p < 0.001$) scores further confirm that embedding explicit levels of iconographic interpretation directly prevents the model from generating decoupled or superficial visual hybrids. As reported in Table 5, with all calculated dimensions yielding $p < 0.001$, the null hypothesis is confidently rejected, demonstrating that the structural improvements derived from taxonomy-guided prompt engineering are highly robust and statistically significant.

4.2 Qualitative expert commentary

Thematic coding of the evaluation panel's qualitative feedback strongly supports the quantitative shifts. The resulting kappa coefficient of 0.82 indicates 'substantial to

Table 6 Empirical ablation scoring profiles across prompt modalities

Performance assessment metric	Baseline condition (SPC)	Length-matched control (LPC)	Framework condition (EPC)	Net framework gain over LPC (%)
Morphological accuracy	2.9	3.1	4.6	+48.4
Material authenticity	2.6	2.8	4.7	+67.8
Semiotic alignment	2.4	2.5	4.5	+80.0
Cultural integrity	2.7	2.9	4.8	+65.5

near-perfect' inter-rater reliability, indicating that the observed enhancements in cultural output were uniformly recognised across both academic and practical craft domains, ruling out individual evaluator bias. The data consolidated into three dominant macro-themes:

Theme 1: Structural Integration versus Surface Application. The expert panel noted that baseline SPC images frequently treated cultural patterns as flat, superficial decorations that appeared digitally printed, overlaid, or sprayed onto the asset surfaces. Hence, the EPC outputs demonstrated an internal construction logic native to the craft medium. *"Image B [EPC] portrays real beading logic and physical hand-tension; Image A [SPC] can be seen as decorative but lacks material truth."* Artisan Evaluator.

Theme 2: Epistemological Fidelity versus Superficial Literalism. In multiple baseline instances, the SPC produced overly literal visual interpretations (e.g., rendering anatomically realistic, three-dimensional trees when prompted with plant-based terms). In contrast, the EPC outputs consistently conformed to the abstract-geometric or phytomorphic design conventions dictated by authentic indigenous *Dayak* epistemology.

Theme 3: Medium-Specific Craft Attributes. Practising artisans highlighted that the EPC outputs successfully captured highly subtle technical execution traits in rattan basketry and textile weaving. These included uniform structural strip alignments, realistic variations in natural dye absorption across organic fibres, and consistent physical weave tensions, features virtually absent in the SPC baseline runs.

4.3 Controlled ablation considerations and empirical validation

To verify if performance gains stem directly from the structural taxonomy or are an artefact of increased word volume, an empirical ablation test was conducted. The framework (EPC) was tested against an experimental LPC that matched the EPC's exact token density (167.7 vs 170.1 mean tokens) but stripped away all taxonomic classifications, hierarchical semiotic variables, and material boundary tags, replacing them with arbitrary, unorganised decorative descriptors. The panel evaluated the ablated outputs across the same four performance dimensions. The quantitative comparisons are detailed in Table 6.

The empirical results reject the hypothesis that text volume dictates cultural precision. Adding unstructured adjectives in the LPC condition produced negligible improvements over the baseline SPC, shifting the Morphological Accuracy marginally from 2.9 to 3.1, and Cultural Integrity from 2.7 to 2.9. While the LPC outputs displayed high image crispness and fine contrast details due to the density of descriptive adjectives, the model suffered from severe architectural confusion. Without explicit geometric boundary tags, the long descriptive prompts often led the model to hallucinate pan-indigenous design styles (blending *Iban* patterns with Polynesian line placements). Furthermore, without structural material rules, the LPC repeatedly generated physically impossible textures, such as trying

to render warp-ikat patterns onto solid bamboo basket weaves. In contrast, the framework condition (EPC) achieved high scores across all areas (all dimensions ≥ 4.5). Because the EPC matches the LPC's token length, this experiment isolates semantic taxonomy as the causal factor driving output authenticity, proving that structural parameters, rather than word volume, successfully control the diffusion model's latent space.

5 Discussion

The findings of this study demonstrate that taxonomy-guided vernacular prompt engineering can significantly enhance the cultural specificity, morphological accuracy, and semiotic coherence of AI-generated indigenous motifs during inference-stage image generation. Compared to the SPC, the EPC consistently achieved higher performance across all evaluation dimensions, including morphological accuracy, material authenticity, semiotic alignment, and cultural integrity. These results indicate that culturally structured prompt systems can function as an effective inference-level governance mechanism for generative AI in indigenous heritage contexts. This study contributes to ongoing discussions on responsible generative AI by demonstrating that cultural accuracy is not solely dependent on model scale, computational power, or visual fidelity, but is strongly influenced by the semantic structure of prompt construction. Generic prompting approaches frequently produced pan-tribal visual hybrids, superficial decorative interpretations, or material inconsistencies that were misaligned with Sarawak indigenous visual logic. In contrast, the taxonomy-guided framework constrained the diffusion process through ethnographically derived descriptors, including ontological categories, vernacular motif identifiers, symbolic meanings, and medium-based constraints. This structured semantic encoding enabled the model to generate outputs that more closely reflect the formal and symbolic logic of *Dayak* material culture.

The findings further reinforce the importance of semiotic embedding in AI-supported cultural preservation. Indigenous motifs function not merely as decorative forms but as structured visual systems that encode cosmology, social hierarchy, ecological relationships, and collective memory. By integrating pre-iconographic, iconographic, and iconological layers into the prompt architecture, the system enables generative models to move beyond surface-level stylistic imitation toward culturally grounded representation. This demonstrates that structured prompt engineering can support epistemological fidelity by preserving relationships between form, meaning, and cultural function. A key contribution of this study is the reconceptualisation of taxonomy as a semantic boundary mechanism within generative AI workflows. Rather than serving solely as a classificatory tool, the proposed taxonomy operates as an inference-stage constraint system that governs how diffusion models navigate the latent visual space. Since large-scale diffusion models are trained on globally aggregated datasets, they tend to reproduce dominant visual patterns and generalised “tribal” aesthetics. The integration of structured vernacular descriptors reduces this bias by anchoring generation within culturally specific semantic and visual rules. This provides a lightweight alternative to an inference-only framework by embedding cultural governance directly into the prompting process.

The ablation analysis further strengthens this interpretation. Although length-matched descriptive prompts achieved comparable visual sharpness and aesthetic complexity, they consistently failed to preserve structural authenticity, material logic, and cultural specificity. Without taxonomy-based structuring, models tended to generate hybridised or geographically inconsistent motifs, as well as physically implausible material

representations. These results confirm that improved cultural fidelity is not driven solely by prompt length, but by the presence of structured semantic and hierarchical encoding within prompts. Beyond technical performance, the study has broader implications for digital heritage preservation and participatory AI development. The framework demonstrates potential as a collaborative tool for artisans, educators, researchers, and cultural institutions engaged in documenting and revitalising indigenous knowledge systems. By embedding ethnographic knowledge into computational workflows, the system supports intergenerational knowledge transmission and the digital continuity of endangered cultural motifs. However, the study also emphasises that such systems must remain grounded in participatory governance, where indigenous communities act not only as data sources but as active knowledge holders and co-designers of AI systems.

Several limitations should be acknowledged. First, the evaluator sample size ($N=6$) is relatively small, and although it includes both scholars and practitioners, the findings should be interpreted as exploratory validation rather than statistically generalisable results. Second, the framework is currently limited to Sarawak *Dayak* motifs, and further validation across additional indigenous cultural systems is required. Third, while the ablation study addresses prompt length effects, further testing across different generative architectures and larger evaluator groups would strengthen robustness. Future research should expand the taxonomy to additional indigenous communities and explore multilingual vernacular prompt systems that accommodate regional dialects and linguistic variation. Further work may also focus on developing community-led interfaces that allow artisans to directly control, evaluate, and co-create generative outputs within ethically governed digital environments. In addition, future studies may examine hybrid approaches that combine taxonomy-guided prompting with carefully controlled model adaptation while maintaining strict ethical safeguards and community consent protocols.

6 Conclusion

This study proposed a taxonomy-guided vernacular prompt framework for culturally aware generation of indigenous *Dayak* motifs using a pre-trained diffusion model. Unlike conventional approaches that rely on parameter-level retraining or fine-tuning, the proposed framework operates entirely at the inference stage through structured prompt engineering. By embedding ontological classifications, vernacular motif identifiers, semiotic descriptors, and medium-based constraints into the prompt construction process, the system guides generative outputs toward greater cultural specificity and morphological consistency. The findings demonstrate that the EPC significantly outperforms baseline prompting approaches across all evaluated dimensions, including morphological accuracy, material authenticity, semiotic alignment, and cultural integrity. These results indicate that culturally structured semantic prompting can reduce visual homogenisation and improve the preservation of indigenous symbolic logic in AI-generated outputs. The study, therefore, contributes to the development of culturally responsible generative AI by demonstrating how indigenous knowledge structures can serve as semantic governance at the inference stage.

Methodologically, the study reframes taxonomy as an active computational control layer rather than a passive classification system. It demonstrates how ethnographic observation, iconographic analysis, and semiotic interpretation can be translated into structured prompt architectures that regulate generative behaviour. This offers an alternative approach to digital heritage preservation that prioritises semantic fidelity,

participatory ethics, and training-free implementation. The study acknowledges that the current framework is exploratory and limited to a specific cultural context with a relatively small validation sample. Nevertheless, the results indicate strong potential for supporting heritage documentation, educational applications, and community-led creative practice. Future development should focus on expanding the taxonomy across broader indigenous contexts, strengthening participatory co-design with local communities, and developing accessible tools that enable cultural practitioners to manage and utilise their digital heritage responsibly. Ultimately, the study demonstrates that generative AI systems do not inherently produce culturally accurate outputs. Instead, cultural fidelity depends on the extent to which indigenous knowledge structures are embedded within the generative process. By integrating structured vernacular semantics into inference-stage prompting, the proposed framework offers a scalable and ethically grounded direction for AI-assisted cultural preservation and indigenous digital heritage representation.

Appendix

Expert validation form

Comparative Evaluation of AI-Generated Indigenous Motif Artefacts

Motif Name: _____
 Artifact Type: _____
 Community: _____

Please evaluate both images independently (the following sections A, B, C, and D need to be filled based on each design separately).

Section A: morphological accuracy—design 1

Criteria	Image A (1–5)	Image B (1–5)
Correct geometric structure	☐	☐
Faithful motif composition	☐	☐
Structural integration into the medium	☐	☐

Section B: material authenticity—design 1

Criteria	Image A (1–5)	Image B (1–5)
Realistic weaving/beadwork logic	☐	☐
Authentic dye/material texture	☐	☐
Absence of digital-print appearance	☐	☐

Section C: semiotic & cultural accuracy—design 1

Criteria	Image A (1–5)	Image B (1–5)
Correct motif interpretation	☐	☐
Alignment with cultural meaning	☐	☐
Avoids literal misrepresentation	☐	☐

Section D: overall cultural integrity—design 1

Criteria	Image A (1–5)	Image B (1–5)
Ethnographic documentation quality	☐	☐
Respectful cultural representation	☐	☐

Final comparative question

Which image more accurately represents the authentic motif within its indigenous material context?

Design 1	Design 2	Design 3	Design 4	Design 5
☐ Image A	☐ Image A	☐ Image A	☐ Image A	☐ Image A
☐ Image B	☐ Image B	☐ Image B	☐ Image B	☐ Image B

Design 6	Design 7	Design 8	Design 9	Design 10
☐ Image A	☐ Image A	☐ Image A	☐ Image A	☐ Image A
☐ Image B	☐ Image B	☐ Image B	☐ Image B	☐ Image B

Comments:

Expert Name: _____

Specialization: _____

Design	A	B
Design 1 <i>maten juhit/ luang mata</i>		
Design 2 <i>kapit ulut</i>		
Design 3 <i>lelingkok betayok</i>		
Design 4 <i>tiger</i>		
Design 5 <i>boton manuk puni</i>		
Design 6 <i>terjat tepun</i>		
Design 7 <i>rojak dien</i>		
Design 8 <i>kelewit</i>		
Design 9 <i>seperut</i>		
Design 10 <i>kejiko/nyatap atap/blade</i>		

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1007/s44163-026-01944-3>.

Supplementary file1 (DOCX 36 KB)

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Author contributions

MHJ—Conceptualization; Methodology; Software; Formal Analysis; Investigation; Resources; Data curation; Writing Original draft; Visualization and Project Administration. JA—Validation, Investigation, Resources, Data curation, Reviewing and Editing.

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Data availability

The data is available upon request from corresponding author.

Declarations

Ethical approval and consent to participate

This study received ethical approval from the Ethics Committee of the Faculty of Applied and Creative Arts, Universiti Malaysia Sarawak (UNIMAS). The research procedures were conducted in accordance with the ethical guidelines and regulations of Universiti Malaysia Sarawak and followed internationally accepted standards for research involving human participants. Informed consent was obtained from all participants before they participated in the study. Participants were informed about the purpose of the research, and their participation was voluntary and anonymous.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Declaration of AI-assisted technologies in the writing process

Declaration of AI-assisted technologies in the writing process During the preparation of this work, the author used ChatGPT as a language assistant to rephrase and refine the text. After using this tool, the author reviewed and edited the content as necessary, taking full responsibility for the publication's accuracy.

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References

1. Barthes R. Roland Barthes by Roland Barthes. Macmillan; 2010.
2. Baxi P, Sr S, Tomar PK, Sharma H, K S, Goyal W & Kulkarni A. Neural networks for classifying Indian folk motifs. *ShodhKosh: J Visual Performing Arts*. 2025;6(3s):499–510. <https://doi.org/10.29121/shodhkosh.v6.i3s.2025.6758>.
3. Davy Ball M. *Betek, tali ngan atap (Knots, string and blades): Production and use of organic utility objects by the Orang Ulu of Sarawak* [Doctoral dissertation, Durham University]. Durham University E-Theses. 2009.
4. De Saussure F. The linguistic sign. In: Innis RE, editor. *Semiotics: an introductory anthology*. Indiana University Press; 1985. p. 28–46.
5. Dev A, Singh S, Kaur A, Neha, Upadhyay S, & Refonaa J. AI-assisted restoration of folk murals. *ShodhKosh: J Visual Performing Arts*. 2025;6(1s):149–159. <https://doi.org/10.29121/shodhkosh.v6.i1s.2025.6643>.
6. Djefal C. Reflexive prompt engineering: a framework for responsible prompt engineering and AI interaction design. In: *Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1757–1768). Association for Computing Machinery. 2025.
7. Haddon AC, Start LE. Iban or Sea Dayak fabrics and their patterns: a descriptive catalogue of the Iban fabrics in the Museum of Archaeology and Ethnology, Cambridge. Cambridge University Press; 2011.
8. Jalil MH & Alison JE. Indigenous culture and sustainable reinterpretation: Bidayuh art and symbolism in contemporary design innovation as a heritage preservation practice—Asian. *J Arts Culture*, 2026;26(3):Article e100.
9. Jalil MH, Lee Abdullah Q, Senin N, Rusdy Wong N, Ngik Hoon L. Nature's echo: biomorphic motifs in Orang Ulu traditional crafts. UNIMAS Publisher; 2025.
10. Keai GK. Inspirasi alam dalam artifak budaya masyarakat Iban di Sarawak: The inspiration of nature in the Iban cultural artefacts at Sarawak. *Sains Insani*. 2021;6(3):15–24.
11. Malarvel MM, Goyal W, Sargam S, Mundada K, Mary AVA & Rathore A. AI for preserving indigenous folk art patterns. *Shodh-Kosh: J Visual Performing Arts*. 2025; 6(5s):88–97. <https://doi.org/10.29121/shodhkosh.v6.i5s.2025.6900>.

12. Ming Y & Xia X. Generative AI technology for safeguarding intangible cultural heritage: A systematic review. In: Proceedings of the 2025 2nd International Conference on Artificial Intelligence and Future Education (pp. 7–17). IEEE. 2025.
13. Octadion O, Yudistira N, Kurnianingtyas D. Synthesis of batik motifs using a diffusion-generative adversarial network. *Multim Tools Appl*. 2025;84(7):3407–38.
14. Odeke LW, Kirui AK. Reclaiming the sonic archive: AI, data sovereignty, and the future of Mijikenda music. *J Visual Performing Arts*. 2025;3(1):53–62. <https://doi.org/10.58721/jypa.v3i1.1516>.
15. Panofsky E. *Perspective as symbolic form*. Princeton University Press; 2020.
16. Pusadan M, Laila R, Pratama SA. Artificial Intelligence untuk identifikasi motif tenun tradisional Sulawesi Tengah. *Bomba: Jurnal Pembangunan Daerah*. 2025;5(1):24–32. <https://doi.org/10.65123/bomba.v5i1.93>.
17. Read J. *Assessing vocabulary*. Cambridge University Press; 2000.
18. Rosli NH, Anak Tugang N, Binti Mohd Safar NWI, AP Bahari U. The uniqueness of the motif design in the community of Uma Ukit Belaga, Sarawak. *Int J Appl Creat Arts*. 2021;4(1):55–67. <https://doi.org/10.33736/ijaca.4208.2021>.
19. Roy K. Indigenous knowledge meets AI: a hybrid mode for biodiversity conservation. *J Inf Syst Eng Manag*. 2025;10(1):681–92.
20. Sánchez-Martín J-M, Guillén-Peñafiel R, Hernández-Carretero A-M. Artificial intelligence in heritage tourism: innovation, accessibility, and sustainability in the digital age. *Heritage*. 2025;8(10):428. <https://doi.org/10.3390/heritage8100428>.
21. Sapun A, Misdih MB, Jusilin HB. Manifestation of cultural heritage and symbol of celebration in the Babulung festival of the Bisaya people in Limbang, Sarawak. *Jurnal Gendang Alam (GA)*. 2024;14:26–39.
22. Seredkina NN. Revisiting methodological principles of the cultural-semiotic approach in studying the art of indigenous peoples of the North, Siberia and the Far East. *J Siberian Federal University. Humanities Soc Sci*. 2014;7(8):1346–1358.
23. Shen M, Shen Y, Liu F, Jin J. Prompts, privacy, and personalised learning: integrating AI into nursing education—a qualitative study. *BMC Nurs*. 2025;24(1):470.
24. Shukla N, Tiwari V & Bairwa AK. Kaarigar: region-specific motif generation using stable diffusion for customizable textile design. In: 2025, *IEEE International Conference on Advanced Computing Technologies (ICACT)* (pp. 94–99). IEEE. 2025.
25. Siliutina I, Tytar O, Barbash M, Petrenko N, Yepyk L. Cultural preservation and digital heritage: challenges and opportunities. *Amazon Investig*. 2024;13(75):262–73.
26. Sumathi G & Devi M. Inpainting of damaged temple murals using edge-and line-guided diffusion patch GAN—frontiers. In *Artificial Intell*. 2024;7:1453847.
27. Tagie G, Merman H & Ibrahim NA. The rich legacy of Iban's tattoo motifs on contemporary craft. *Int J Appl Creative Arts*. 2025;8(2):23–40. <https://doi.org/10.33736/ijaca.8868.2025>.
28. Tiribelli S, Pansoni S, Frontoni E, Giovanola B. Ethics of artificial intelligence for cultural heritage: opportunities and challenges. *IEEE Trans Technol Soc*. 2024;5(3):293–305.

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