INVASION OF THE SPARKLES: UNPACKING AI'S VISUAL RHETORIC

1 Toolify.ai Dataset Construction

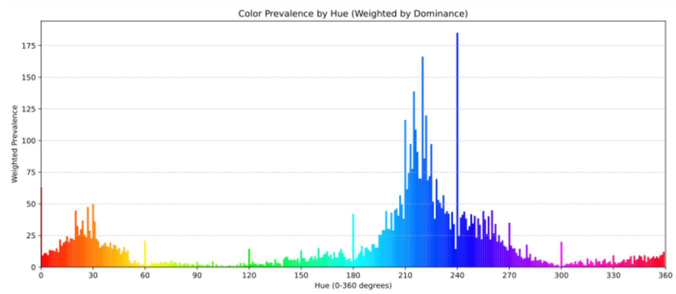
Toolify.ai was chosen over app download rankings due to the challenges of scraping app stores, including paywalls, dynamic content restrictions, and the need for user authentication, whereas websites offer a more accessible and complete representation of AI tools. For that we:

A. Took the tool-names from the region-rankings [28925]
B. Removed Duplicates [8608]
C. Retrieved domain names by querying the DuckDuckGo API and selecting the first search result
D. Captured scrollshots using Playwright [7713]
E. Filtered out erroneous captures (unclosed pop-ups, format outliers, reCAPTCHA, content loading) [6318]

2 Analysis

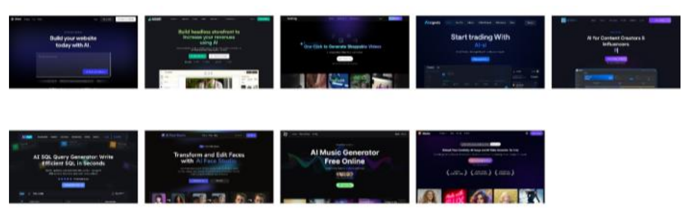
Color Analysis: To analyze the visual identity of AI tools in the dataset, we first focused on color prevalence. Traditional RGB representations were replaced with the Hue-Saturation-Value (HSV) space for more intuitive analysis and visualization of perceptual color relationships. To isolate meaningful hues, we filtered out near-white/black pixels by excluding high-intensity colors (threshold: 90% intensity) and low-saturation colors (threshold: 20% saturation). This emphasized perceptually salient hues while reducing noise from achromatic tones.

We weighted hues by their dominance within each image. Using MiniBatchKMeans clustering, we extracted the five dominant color clusters per image (resized to 256×256 pixels for efficiency). Each hue's contribution was scaled proportionally to its cluster size, ensuring prevalent colors in the dataset were accurately reflected. Aggregating results across 6,318 images produced a hue histogram (0–360°), where bar heights represent the cumulative weighted prevalence of each hue.



Visual Clustering: To identify patterns in website design, we employed a deep learning approach using VGG16—a convolutional neural network pre-trained on ImageNet—to extract high-level visual features from the 6,318 normalized screenshots (360 × 640 px). The model's final convolutional layer generated spatial feature maps capturing layout, texture, and compositional patterns while discarding domain-specific object recognition capabilities as would be needed for the systematic detection of sparkles or other signifiers of magic.

For computational efficiency, we reduced the 512-channel feature maps to 50 principal components using PCA. These compressed representations were clustered into 20 thematic groups via K-Means (n_init=10), optimized to balance granularity and interpretability. Cluster coherence was validated through t-SNE visualization (perplexity=30), which projected high-dimensional features into a 2D space while preserving relative distances.



Linguistic Analysis: To investigate how AI tools linguistically construct narratives of enchantment, we analyzed textual content extracted from scrollshots using Tesseract optical character recognition (OCR). Then we quantified the relative prevalence of enchantment-related terms against (1) functional descriptors (intelligent) and universal adjectives (amazing) within the toolify.ai dataset and (2) the prevalence of the terms in external textual corpora.

Julius Pfundstein | julius.pfundstein@gmail.com | Center for Digital Participation