

Colour-Based Movie Recommendations

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Abstract

While the association between colour and emotion is well-documented and the significance of colour in cinema is widely acknowledged, there remains a lack of functional tools for retrieving or recommending movies based on their colour palettes. This paper explores the integration of colour palettes as a feature in movie recommendation systems, moving beyond traditional metadata. We present four core contributions: first, a comprehensive literature review synthesizing colour palette applications, generation techniques, and colour-emotion associations. Second, we evaluate a prototype application that utilizes palettes for movie recommendations; a USE (Usefulness, Satisfaction, and Ease of Use) questionnaire confirms a statistically significant trend toward the tool being perceived as useful, simple, and exciting. Third, we conduct a comparative study between Netflix, Amazon Prime Video, and our palette-based recommendation algorithm on iconic colour-graded movies. While results underscore the market dominance of Netflix, our method produces better movie recommendations than Prime Video in 50% of our study trials, and an analysis of user justifications reveals a clear consideration for colour. Moreover, a statistically significant majority of participants expressed a direct interest in colour-based recommendation features. Finally, we compare a palette-based refinement of TMDb movie recommendations against standard TMDb recommendations. Statistical analysis demonstrates a significant user preference for recommendations narrowed by colour-matching. Together, these findings validate colour as a viable and desired metric for enhancing digital media retrieval.

CCS Concepts

• **Applied computing** → **Media arts**; Fine arts; • **Computing methodologies** → **Image processing**; *Perception*; • **Information systems** → **Video search**; *Image search*; **Retrieval effectiveness**; **Similarity measures**; **Novelty in information retrieval**.

Keywords

digital image processing, image retrieval, video retrieval, colour palettes, human-computer interaction

ACM Reference Format:

Andreea Pocol, Lesley Istead, and Craig S. Kaplan. 2026. Colour-Based Movie Recommendations. In *Proceedings of Graphics Interface ('GI')*. ACM, New York, NY, USA, 10 pages. <https://doi.org/XXXXXXX.XXXXXXX>

1 Introduction

Palettes are useful for feature extraction, information retrieval, and comparison because they remove unimportant information, distilling the source from which they are extracted to its core or essence.

While our focus in this paper is on deriving colour palettes from video, specifically movie trailers, and using these in recommendations, there are many other uses for colour palettes. They can be applied to interior design [32], website / user-interface design [8, 23], product design [12], advertisement [45], document templates [23, 25], and even urban planning [18].

They can also be used for palette-based colour transfer, one application of which is film promotion. A film's colour scheme can be applied to automatically colour grade [29, 47, 48] various promotional materials, including movie posters, merchandise, web pages, Snapchat filters, and more, in order to effectively convey the mood of the film. In 2022, for example, the brand NYX Professional Makeup collaborated with *Avatar: The Way of Water* to release multiple makeup palettes and sets inspired by the colours of the movie. This includes: an eyeshadow palette featuring 24 of the 'saturated pigments' and "bio-luminescent hues found only in the lush jungles, vibrant forests and colourful seas of Pandora," three 'glass-like duo-chrome' lip glosses in the 'electric' colours 'Shimmering Waters,' 'Bioluminescent Glow,' and 'Illuminate,' two vibrant lipstick shades "inspired by the regal Neytiri and Ronal," three highlighter sticks in bio-luminescent shades 'Seagrass,' 'Sunrise Banshee Ride,' and 'Coral Reef,' and more [38]. R.E.M. Beauty also released makeup styled and packaged in the complementary green-and-pink colour scheme of *Wicked: For Good*. Their website describes them as "spellbound shades straight from oz; bewitching hues, transformative textures, and shimmering duochromes, inspired by wicked: for good, now in theaters" [34].

In the field of computer graphics, a colour palette can be used as an 'index map' or 'colour map' in colour image quantization for image compression, optimization, or analysis [7, 10]. In the fashion industry, colour palettes can be used to process fashion-related images and analyze trends [1, 7]. Other artistic applications beyond image recolouring [2, 37] include stylization, beautification, creation, and data visualization [7]. Colour palettes can also be used to explore the use of colour "in artistic expression and aesthetics," such as film [7], as we are primarily focused on doing.

We will be discussing the use of colour palettes in video retrieval for the purpose of movie recommendations. The widespread fascination with cinematic visual style is evident in the popular curation of films recognized for their distinctive colour palettes on platforms

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ACM ISBN XXX-X-XXXX-XXXX-X/2026/06

<https://doi.org/XXXXXXX.XXXXXXX>

like IMDb,¹ as well as in the creation of expert colour arrangements by professional practitioners [14]. There is evidence on social media of people finishing a movie and seeking other movies with the same ‘vibe’, ‘aesthetic’, or ‘atmosphere.’² One of the original posters explicitly states that it is not the plot they are referring to, and the other expresses their frustration at their search only yielding movies that match in terms of genre. The growing popularity of social media accounts dedicated to cinematic aesthetics, such as [@colorpalette.cinema](#) on Instagram, underscores a broader cultural fascination with evaluating motion pictures through the lens of their chromatic profiles.

While it may appear that film posters offer a representative colour palette for a film, this assumption is often empirically inaccurate. These promotional tools are designed chiefly for the purpose of grabbing attention. For instance, the iconic bright orange aesthetic of the *Vertigo* (1958) poster fails to reflect the specific psychological use of deep greens and saturated reds that define the film’s actual cinematic identity. Furthermore, even if posters were chromatically accurate, there currently exists no systematic mechanism to identify the most similar aesthetic match for a given poster, just as there is no existing infrastructure to facilitate the best chromatic discovery for a film itself. Other examples are given in community discussions.³

In 2024, YouTube rolled out an experimental feature allowing users to filter their feed by video thumbnail colour [39]. We posit that this approach should be extended to the cinematic domain, given the previously cited evidence of a public interest that remains largely unaddressed by manual, ad-hoc curation. Instead, platforms like Netflix and Prime Video typically use *collaborative filtering* (CF), which “can be described as the process of automatically predicting user interests by collecting information about the tastes or preferences of many users” [33]. This paper explores the research question: *how can colour be used to assist in movie discoverability?*

Section 2 starts by explaining how colour has been shown to influence emotion, making it a useful cinematographic tool. It then outlines colour palette generation – existing methods of extracting colours from digital media – as well as methods for comparing colour palettes. Section 3 explains our proposed colour-based movie recommendation algorithm. Section 4 shows how colour compares and integrates with current movie recommendation landscapes, based on the results of three user studies we conducted.

2 Literature Review

2.1 Colour-emotion association

The professional significance of film colourists underscores the critical role of colour in cinematic storytelling.

The relationship between colour and emotion has been the subject of longstanding interest, and is a foundational element of visual communication, functioning through both innate biological responses and acquired cultural metaphors [9, 22]. This ‘Universalist’ versus ‘Culturalist’ debate is central to colour psychology:

while some associations appear to be hard-coded into human physiology, others are products of linguistic and social conditioning [5, 11]. A 2025 meta-analysis of 132 studies involving over 42,000 participants confirmed that while specific cultural nuances exist, there is surprising global uniformity in linking colour to mood [13].

Early foundational research established consistent mapping between specific hues and emotions [24, 26]. Wexner (1954) demonstrated that these pairings remain robust regardless of gender, while D’Andrade and Egan (1974) found striking consistency between indigenous Mexican and urban American subjects, suggesting a psychological baseline that transcends modernization [5, 42]. Developmental studies further suggest this ‘colour vocabulary’ is not slowly learned but emerges early in childhood, with children consistently matching bright hues to positive affects and dark hues to negative ones [3].

However, modern research highlights that these associations are often many-to-many rather than one-to-one [22]. For instance, red is a polarizing hue, simultaneously representing positive states like passion and love and negative states like danger and anger [22]. Additionally, saturation and brightness (chroma and value) often play a larger role in emotional intensity than hue alone; warm, vibrant, highly saturated colours are universally linked to positive emotions, while desaturated tones are associated with negative emotions [43].

In the context of cinema, colour is a deliberate tool used to craft emotional experiences and establish narrative atmosphere [17, 21, 46]. Empirical studies in film analytics have shown that dominant colour ratios and colour intensity can predict the mood of a scene with up to 80% accuracy [40]. Warm colours (oranges, reds) are typically utilized to heighten emotional intensity or positive valence, whereas cold colours (blues, teals) are effective for conveying low-valence, sombre contexts [43]. This underscores the potential for colour palettes to serve as a primary metric for content-based movie recommendation and discovery.

2.2 Colour palette generation

A colour palette is an abstract piece of data, not necessarily a rectangle of coloured tiles or swatches arranged in a horizontal row, as is the implicit assumption in most papers. Rather, it is a curated, limited collection of colours, whether a set or sequence, ordered or unordered. Yang et al. found some evidence in their 2020 paper that the order (or arrangement) of the colours in colour palettes affects the perceived visual difference between them [44]. A palette can be extracted from a piece of visual media – such as a video or image – or it may be contrived.

2.2.1 K-Means. K-Means is the most common algorithm for colour palette extraction, partitioning pixels into k clusters in 3D space. The algorithm iteratively reassigns pixels to the nearest of k pre-defined centroids, updating each centroid to the arithmetic mean of its assigned points until convergence. While mathematically reliable and fast for small k , it requires the number of colours to be specified in advance and may ignore small, perceptually significant details that lack sufficient “mass”. In Scikit-Learn, the default `n_init=10` runs the process ten times to avoid poor results from random initializations, while the K-Means++ variant uses ‘smarter’ initialization to accelerate convergence.

¹For example, <https://www.imdb.com/list/ls505582709/>

²Such as: <https://www.reddit.com/r/twilight/s/9ij05suG0l>, and <https://www.reddit.com/r/twilight/s/RPsA3YPYF6>

³https://www.reddit.com/r/Letterboxd/comments/1jxu3ij/movie_posters_that_do_not_match_the_tone_of_the/

2.2.2 Median Cut. Using a ‘divide and conquer’ approach, Median Cut places all pixels into an initial 3D bucket and recursively splits it. The algorithm identifies the colour channel with the largest range, sorts the pixels, and divides the bucket at the median value to ensure an equal pixel count in each resulting cube. This continues until the desired number of colours is reached, with the median RGB value of each cube forming the final palette. Although extremely fast, it can produce ‘muddy’ results in images with wide gradients, as it acts as a volume-splitter rather than a density-finder.

2.2.3 Mean Shift. Mean Shift is a non-parametric, density-based algorithm that treats colour space as a landscape of peaks and valleys. It iteratively shifts a window (kernel) toward the ‘centre of gravity’ of local pixel density until it reaches a peak, or mode. A key advantage is its ability to discover the ‘natural’ number of colours without a predefined k , though it is computationally expensive and slow on high-resolution imagery.

2.2.4 Octree Quantisation. This memory-efficient method uses a tree structure with eight subnodes per level to represent the colour space. Pixels are inserted to a maximum depth of eight levels; as the tree grows, similar colours share branches, while deeper nodes represent more precise hues. If the leaf count exceeds the target palette size, the deepest nodes are merged into their parents. While effective at handling diverse colours, it prioritizes technical memory optimization over aesthetic visual harmony.

2.2.5 DBSCAN. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) identifies clusters based on point density, allowing it to ignore ‘noise’ like compression artifacts. It uses two parameters: ϵ (search radius) and MinPts (minimum neighbours required to form a cluster). While excellent for grainy images, it struggles with varying densities—such as a sharp subject against a blurred ‘bokeh’ background—where a single ϵ value may fail to bridge gaps in thin density regions without accidentally merging distinct subjects.

2.2.6 Histogram Thresholding. Unlike clustering, this strategy creates a 3D colour histogram and divides the space into ‘bins’ to identify local maxima as palette anchors. While faster than K-Means as it processes histogram data rather than individual pixels, it is susceptible to aliasing; a dominant colour sitting between two bins may be split or missed entirely. Additionally, it lacks spatial context, treating concentrated blocks of colour and scattered noise identically.

2.2.7 Image Segmentation. Segmentation-based extraction identifies semantic regions (e.g., ‘person’ vs. ‘background’) using artificial intelligence to determine what ‘things’ are in an image. For each identified segment, the algorithm calculates a representative mean or median colour, weighting them by importance or size. This method provides high colour purity and contextual awareness, though it requires significantly more processing power than mathematically simpler clustering methods.

2.2.8 Binned-KMeans. We previously introduced Binned-KMeans, a novel colour palette generation method for videos, which is step-sorted for easier comparison, focuses exclusively on bold and memorable colours, is conducive to colour analysis in its layout, and uses a corrected saturation weighting formula from previous work [31].

Figure 1 shows examples of Binned-KMeans palettes overlaid onto the first frame of each of four short (10-second) movie clips. Note the ability of the palettes to capture the essence of the scene while omitting unmemorable tones. For example, there are more beige pixels in the *Saving Mr. Banks* scene than any other colour, but the beige wallpaper fades into the background; the salient regions are the deep brown suit skirt set, the pine green lacquer gift bow and couch, the yellow stuffed animals, and the bright red apples.

2.3 Colour palette comparison

Colour palette comparison is a relevant problem because colour palettes represent images, which in turn may be the frames of a video; therefore, comparing colour palettes is useful in comparing images, which is useful in comparing videos (by comparing the constituent frames). In turn, image comparison is useful for applications such as online and/or mobile shopping (because some items are difficult to describe in terms of textual attributes) [1]. Video comparison is useful for movie recommendation (e.g. Netflix) or video recommendation (e.g. YouTube). Palette comparison is useful in evaluating different palette generation methods compared to a human-generated, ground-truth palette [41]. Graphic designers may wish to either create or retrieve similar colour schemes which adhere to a particular concept [36].

We want to be able to measure the similarity between colour palettes, a problem equivalent to the distance between sets [4].

2.3.1 Single Colour Difference Model. Pan et al. [28] propose three colour palette comparison methods, all using the Euclidean distance ΔE colour difference formula. The *Single Colour Difference Model* characterizes an entire colour palette by a single representative value, derived from the mathematical average of all colours within that set. This method assumes some degree of cohesiveness between the colours, which is not a reliable assumption for many applications, including ours. It uses Euclidean colour distance.

2.3.2 Mean Colour Difference Model. This model assumes that we are comparing 2 n -colour palettes. Each colour in one palette can form a pair with each colour in another palette. Thus, each colour in one palette will form n colour pairs with the n colours in the other palette. The CIELAB colour difference is calculated between each colour pair, resulting in a set of n^2 colour pairs/difference values. The mean colour difference is obtained by averaging the n^2 colour differences to represent the colour difference between the two colour palettes.

2.3.3 Minimum Colour Difference Model (MICD). This model finds, for each colour i in one palette, the corresponding colour j in the other palette that is the closest match, which minimizes $\Delta E_{i,j}$. This is repeated in the opposite direction. It then yields the average of these ΔE differences. Note that the mapping is not necessarily one-to-one.

2.3.4 Hausdorff distance (DHD). This metric identifies the degree of divergence between two sets by determining the distances between the most proximal point pairs across both sets and then selecting the longest / maximum value among them. However, because this metric is notably susceptible to the influence of outliers or data noise, several more robust alternatives have been developed.



Figure 1: Binned-KMeans palettes for four 10-second movie clips (only the first frame of each clip is shown). From left to right: *Saving Mr. Banks*, *Snake Eyes*, *Pride*, and *The Maze Runner*.

These include the modified Hausdorff distance (MHD), the least trimmed square Hausdorff distance (LTS-HD), and the Minimum Colour Difference (MICD) metric. MICD is more robust because it averages the distances of all colours in the palette rather than relying on a single maximum discrepancy.

2.3.5 Colour-based Earth Mover’s Distance (CEMD). MICD does not consider the cost of moving the entire colour distribution, only the shortest path for each colour. So, in theory, all colours from one palette could map to the same colour in the second palette, and the cost of this directed matching would be lower than it perhaps should be. *Colour-based Earth Mover’s Distance (CEMD)* [36] focuses on colour distributions rather than just individual colour comparisons. The EMD represents the minimum work required to align two distributions, such as colour palettes. It aims to minimize the cumulative product of individual colour flows and their respective distances, iteratively evaluating the objective function to determine the optimal match. This method was popularized by Yossi Rubner’s Stanford University doctoral thesis titled “Perceptual Metrics for Image Database Navigation” [35], specifically Chapter 4, which discusses the metric’s application in measuring image similarity. CEMD was used by [16], who developed an image-searching method that finds images based on a query colour palette.

2.3.6 Dynamic Closest Colour Warping (DCCW). This method by Kita et al. [15] recognizes that the order of colours in a palette is a critical factor in comparison, as it influences how humans perceive the differences or similarities between palettes. However, because colour is a multi-dimensional vector, no single, universally definitive method for ordering a palette exists. To address this, the creators of DCCW suggest a spatial strategy for organizing colours that navigates the 3D graph of a palette’s colour points, allowing for the concurrent evaluation of both hue and brightness. Following this step, they measure the distances between colours in conjunction with their specific sequence. Ultimately, they reorganize the palettes through a sorting process that evaluates both the proximity of colours and their relative positions within the order. When comparing colour a_i (from Palette A) to Palette B, the algorithm does not just look at the nearest colour b_j . It looks at the interpolated segments (edges) connecting b_j to b_{j+1} . The final similarity score is the sum of these ‘closest distances’ along the warping path of the sorted palette, which they solve using dynamic programming. The ‘warping’ part of the algorithm requires a continuous target to warp toward, a smooth line in 3D space.

2.3.7 Minimum bipartite matching error. The method matches the colours in one palette to the colours of the other to achieve the minimum total error [19]. This is not necessarily a ‘perfect’ – or

one-to-one – mapping. The number of colour mappings where the error or distance falls below a defined threshold is computed and used to quantify the similarity between the two palettes [19].

2.3.8 Merged palette histogram similarity measure (MPHSM). When $N = 1$, we have 1-colour palettes and the traditional colour-difference problem, which has been extensively explored; when N becomes very large, the problem becomes one of image similarity rather than palette similarity. Colour histograms are a valid approach if palettes are large enough to approximate an actual image, since this method is usually used to compare images. After the colour distributions in the two palettes are plotted as histograms, the histograms can be compared using one of the following histogram comparison methods: Hellinger, Correlation, Intersection, or Chi-Square. Given that the two input palettes may vary in both size and chromatic distribution, Po and Wong [30] developed a merged palette histogram similarity measure (MPHSM) to project them onto a unified ‘common ground’ or standardized set of histogram bins.

2.3.9 The Hungarian method. The Hungarian method (Kuhn-Munkres algorithm) treats the problem of palette comparison as an assignment task with a cost matrix [41]. The Kuhn-Munkres algorithm is the canonical and most efficient method for guaranteed exact solutions to the Square Assignment Problem (where the number of agents equals the number of tasks equals n). It delivers the optimal (minimum cost) assignment in polynomial time, specifically $O(n^3)$. The Kuhn-Munkres algorithm pairs the colours from one palette with the colours from the other palette so that the sum of the elements in the cost matrix is smaller than the sum of the elements representing any other assignment or pairings. Various matrix operations allow for the calculation of only n colour differences on average, but $2n$ in the worst case. Unlike CEMD, the Hungarian method makes a *binary* assignment; each colour in one palette is assigned to one colour in the other palette, and no colour is assigned to more than one colour in the other palette. One downside of this is that both palettes being compared must be the same length; a square matrix is required.

3 Methodology

This section outlines our proposed colour-based movie recommendation algorithm.

We previously developed a novel palette generation method, Binned-KMeans [31], which we have shown outperforms traditional K-Means clustering at generating palettes based on colour-rich movie trailers (see Figure 2).

Now, we combine this logic with Colour-Based Earth Mover’s Distance (CEMD) for palette comparison, due to its ability to handle



Figure 2: Unlike our method (top), standard K-Means (bottom) fails to capture *Avatar*’s signature purple and green, instead producing a palette dominated by forgettable greys.

different palette sizes and its focus on distributions. This is similar to Kita et al.’s [16] palette-based image-searching method. We use this retrieval method to construct a colour-based movie recommendation algorithm. We have curated a dataset of palettes representing approximately 73,000 movies, along with their metadata.

Our proposed recommendation algorithm is as follows. First, a target movie is selected. In our first proposed method, we fetch the list of genres and filter all movies in our dataset to keep only those with two or more genres in common. Then, the colour palettes for all of these candidates are compared to the colour palette of the target movie. The movies with the lowest CEMD dissimilarity scores are presented to the user. An example of the top two colour-based recommendations for the iconically teal-orange *Asteroid City* (genres: Comedy, Drama, Romance) is given in Figure 3.

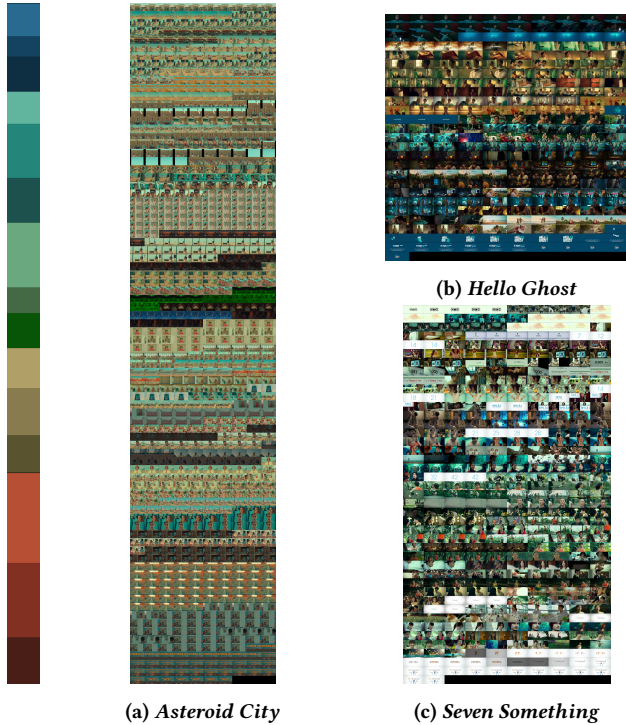


Figure 3: The palette for *Asteroid City*, and every tenth frame of the trailers for *Asteroid City* and CEMD-based recommendations.

We designed a web application prototype described in [31]. This application makes movie colour palettes explainable by showing corresponding trailer frames with colour masks applied, and also allows users to search for movies by dominant colour. For each

movie, our proposed recommendation algorithm is used to retrieve three movie recommendations. A user study on user perception of this application is described in section 4.1.

In section 4.2, we compare the performance of our algorithm to that of Amazon Prime Video and Netflix in a user study.

In section 4.3, we present the results of another user study assessing the effectiveness of integrating colour as a feature in TMDb’s movie recommendation system.

4 Results

4.1 Evaluating the web application

We felt that users should be able to search for movies by colour, and developed a web application prototype to gauge user interest in this option. We conducted a user study to evaluate this tool, which was distributed on Reddit. Importantly, no incentive – financial or otherwise – was offered for participants of our study. The USE questionnaire was taken from Arnold Lund’s paper, “Measuring Usability with the USE Questionnaire” [20]. A paper by Oliveira et al. presents iFelt, a web app which classifies movies by dominant emotion, as measured by biosensors fitted to viewers [27]. The tool is evaluated by ten recruited subjects using Lund’s proposed USE questionnaire. Because of the similar natures of our undertakings, we decided to model our own user study evaluation on Oliveira et al.’s.

We received 33 responses. After a guided exploration of the app showcasing its key features, we asked participants to answer three questions: “Usefulness: Are the results provided by the tool useful?”, “Satisfaction: Do you find the tool fun to use?”, and “Ease of Use: Do you find the tool easy to use?”, on a Likert scale. In each category, there was a clear, statistically backed preference towards the higher end of the scale ($\chi^2(4) = 20.48, p = 0.0006$ for Usefulness, $\chi^2(4) = 15.33, p = 0.0039$ for Satisfaction, $\chi^2(4) = 9.88, p = 0.0425$ for Ease of Use) in the Chi-Squared Goodness-of-Fit tests. While the Chi-Squared test confirms the score distribution is non-uniform, One-Sample Wilcoxon Signed-Rank tests further demonstrate that user experience is significantly above neutral, with median scores for Usefulness, Satisfaction, and Ease of Use all exceeding the value of 3 ($p < 0.05$). Specifically, 60.6% of users ranked the tool at least 4/5 in the Usefulness category. 66.7% of users ranked the tool at least 4/5 in the Satisfaction category. 63.6% of users ranked the tool at least 4/5 in the Ease of Use category. The mode was 4 out of 5 in each category. Users described it as ‘nice’, ‘innovative’, ‘very interesting’, and ‘useful’, one user writing that they ‘hope it can become a popular tool and save time when picking a movie with [their] girlfriend’.

4.2 Comparison of our algorithm to Amazon Prime Video and Netflix algorithms

We propose a rudimentary movie recommendation algorithm based on colour palette similarity and genre. We aim to demonstrate the effectiveness of this algorithm through a user study.

The purpose of this study is to determine whether our algorithm outperforms Netflix and/or Prime Video on movies with notable colour use, as defined by the official Filmworkz ranking. To ensure the algorithm is evaluated against the sophisticated standards of major streaming platforms such as Netflix and Amazon Prime Video,

genre – a conventional element of recommendation engines – was integrated as a primary feature. Our objective is to demonstrate that a simple movie recommendation system based solely on colour and genre can achieve significant efficacy without needing to construct invasive user profiles or relying on complex deep learning architectures and neural networks. We aim to present participants with the trailers of movies using iconic colour grading, and for each movie: the trailer for the top Netflix recommendation, the trailer for the top Amazon Prime Video recommendation, and the trailer for our colour-based recommendation.

To reduce cognitive load, we only presented each user with a random subset of the movies. The objective was to demonstrate that colour-based movie recommendations can be useful to movie viewers and can, in cases where colour is used intentionally, outperform traditional recommendation algorithms.

When designing this survey, it was important to select movies fairly and reasonably. Only when colour is memorable do viewers care to be presented with colour-based recommendations [6]. Colour-based recommendation is not meant to be used in every movie recommendation scenario. Therefore, it should only be applied where colour use is memorable, significant, intentional, or notable. ‘Notable’ colour use is difficult to define and may be subjective. Luckily, Filmworkz has produced a ranking of ‘[The 10 Most Iconic Color Grades in Film](#).’ Not only is there no official rival ranking anywhere on the internet at the time of this writing, but Filmworkz is an authority on the subject because they provide the best tools in the market for colour grading and restoration. We set out to find the top recommended movie for each of these ten movies on both Netflix and Amazon Prime Video.

Crucially, the movies must offer recommendations on both Prime Video and Netflix. From the original list, we could not find *2001: A Space Odyssey*, *Fantastic Mr. Fox*, or *Avatar* on Netflix in November 2025, nor *In the Mood for Love* on Amazon Prime Video. This left us with 6 candidate movies. When identifying the top recommendations on these platforms, we ignore any other movies from the same series. In recommendation systems research, recommending a sequel to its predecessor is considered a ‘trivial’ or ‘identity’ match. Including these would artificially inflate accuracy scores without testing the algorithm’s ability to find latent connections. By focusing on independent titles, we can mitigate this triviality bias and more effectively measure the utility of the Binned-KMeans algorithm in identifying non-obvious, cross-domain visual similarities that would otherwise be obscured by direct series associations. We also filtered against TV show recommendations, considering only movie recommendations. Finally, recommendations must be English titles, as language is an obvious confounding factor which may influence participant responses more than the content of the movies themselves. Controlling for this variable was simply easier than attempting to quantify its impact. All recommendations match the genres of the target movies. Our recommendations match at least two of the three genres returned by OMDB API for the target movies, though Netflix and Prime Video recommendations occasionally use more fine-grained genres found on IMDb. For *Blade Runner 2049*, the Netflix recommendation aligns with the Action genre, while the Prime Video suggestion matches the Drama category. For *Vertigo*, Netflix provides a match for Mystery and Romance, whereas Prime Video aligns with Thriller (specifically, Psychological Thriller). For

Harry Potter and the Order of the Phoenix, the Netflix recommendation matches the Action genre, and the Prime Video selection corresponds to Action and Adventure. For *Twilight*, Netflix suggests a title within the Dark Romance sub-genre, while Prime Video matches on Teen Romance, Drama, and Romance. For *O Brother, Where Art Thou?*, the Netflix recommendation matches Comedy, and the Prime Video suggestion aligns with Adventure. For *Mad Max: Fury Road*, both the Netflix and Prime Video recommendations exhibit a dual match on Action and Sci-Fi. Nevertheless, genre is a potential confounding variable. Table 1 shows the recommendations of the three rival algorithms. Note that the comparison was ‘blind’; users did not know which recommendation came from which source, to preempt any bias concerns.

Our algorithm outperforms Prime Video in 3 out of 6 trials. While this win is not statistically significant, we can say that, in 50% of the trials, a custom algorithm built on only colour and genre performed at the same statistical level as a multi-billion dollar metadata-driven engine. Overall, the results of this study suggest that Netflix outperforms the other algorithms. According to a Chi-Square calculation, this finding is statistically significant ($\chi^2(2) = 6.999, p = 0.0302$) at the $p < 0.05$ level, though not at the $p < 0.01$ level. We employed an ANOVA test to determine if the variation in performance across the three algorithms was statistically significant or attributable to chance. Given the ‘noisy’ nature of user preferences across distinct categories, the resulting p -value (0.195) exceeded the 0.05 threshold. This indicates that while Netflix and Prime Video yielded higher average vote counts, the high variance prevents a statistically significant declaration of a consistent winner across all trials.

We note that the Netflix recommendation algorithm is a highly complex ‘black box’ yielding very sophisticated recommendations. A simple colour-and-genre-based recommendation algorithm cannot replace the complexity of Netflix in a direct comparison. We suggest that colour should be used in conjunction with and not in place of a complex machine learning-based recommendation algorithm. This hypothesis is explored in section 4.3.

The word cloud in Figure 4 illustrates the (optional) justifications our participants gave for the movie recommendation they selected. Word size indicates frequency of occurrence in user responses. Interestingly, “palette” appears as prominent (and, to a lesser extent, also “colour”) despite no indication whatsoever being given in the instructions or description that this survey was about colour palettes. The survey intro was simply: “We are conducting this study as part of a larger study on movie recommendation systems. In this study, you will be presented with a movie trailer and asked to make a recommendation from a list of candidate movies.”

The most useful result of this particular user study was the responses to the optional outro question: “Do you believe that colour could be used to assist in movie discoverability? That is, would you like to see movie recommendation systems incorporate overall colour use/tones of movies in their recommendation algorithms?”

Out of 52 total participants, 37 (71.2%) answered ‘Yes’, 10 (19.2%) answered ‘No’, and 5 (9.6%) answered ‘Don’t know/Don’t use’.

We used a Chi-Square Goodness of Fit test to see if the ‘Yes’ majority is statistically significant. The null hypothesis was that there is no consensus; participants are equally likely to choose any of the three options (17.33 votes each). The Chi-Square Statistic was 34.19, with a p -value of 0.0000000376. The verdict was that, yes,

	Blade Runner 2049	Vertigo	Harry Potter: Order of Phoenix	Twilight	O Brother Where Art Thou?	Mad Max: Fury Road
Genres	Action, Drama, Mystery	Mystery, Romance, Thriller	Action, Adventure, Family	Drama, Fantasy, Romance	Adventure, Comedy, Crime	Action, Adventure, Sci-Fi
Ours	High & Low: The Movie 3 - Final Mission	Replica	Wild Witch	Dorian Gray	The Babylon Out-laws	Rupture
Netflix	Transformers	Rebecca	The School for Good and Evil	Warm Bodies	Asteroid City	Lucy
Prime Video	Ex Machina	The Night of the Hunter	DC League of Super-Pets	Our Fault	Batman (1989)	Jurassic World Re-birth

Table 1: Movie Data Used to Compare Recommendation Algorithms

Primary Movie (ID)	Recommendation (Thematic/Colour): Movie Title (ID)	Colour-based Dissimilarity Score
The Terminal (tt0362227)	Thematic: Love with the Proper Stranger (tt0057263)	30.4728
	Colour: A Lot Like Love (tt0391304)	14.5421
The Boy in the Striped Pyjamas* (tt0914798)	Thematic: Empire of the Sun (tt0092965)	26.6576
	Colour: The Book Thief (tt0816442)	10.8165
Amélie (tt0211915)	Thematic: Paris, 13th District (tt12708658)	28.7650
	Colour: Paris Je T'aime (tt0401711)	12.4584
The Memory of a Killer** (tt0374345)	Thematic: Tightrope (tt0088272)	31.7328
	Colour: Amsterdammned (tt0094651)	15.2575
Mission: Impossible (tt1229238)	Thematic: You Only Live Twice (tt0062512)	27.8786
	Colour: Salt (tt0944835)	11.8584
Limitless (tt1219289)	Thematic: A Scanner Darkly (tt0405296)	25.7996
	Colour: Neverwas (tt0418004)	9.0021

Table 2: Movie Data Used to Test Colour-Based Enhancement of TMDb Recommendation

*Disturbing content in movie and/or recommendation trailer(s).

**Non-English content; some trailers may be unavailable



Figure 4: Without prompting, several participants considered colour and colour palette when choosing a recommendation.

there is a significant consensus. The 'Yes' group (71.2%) is not just a simple majority; it is a supermajority. That is, even if we were to group the 'No' and 'Don't know' responses together as a single 'Non-Yes' category, the 'Yes' votes still significantly outweigh them (37 vs 15).

4.3 Integration of colour into TMDb recommendation algorithm

Perhaps Netflix is too sophisticated to compete with, but we hypothesized that there is room for improvement in the TMDb recommendation algorithm. TMDb is effectively a proxy database that represents the *type* of content Netflix has. Unlike Netflix, however, TMDb is free, has an official API, and is the industry standard for researchers. Conveniently, the API has a [recommendations](#) endpoint and a [similar](#) endpoint, which produce a list of movies that are ‘thematically similar’ to the target movie. The similar endpoint is based on genre and plot keywords (content-based filtering), while the recommendations API uses a user-ratings-based algorithm closer to collaborative-based filtering,⁴ like popular streaming services. We proceeded with the recommendations API, at the suggestion of TMDb staff⁵

⁴<https://www.themoviedb.org/talk/62ce242fd4cc8e004b4f9da0>

³<https://www.themoviedb.org/talk/59efc7fc3a368062004dba>. In practice, the recommendations endpoint seems to be used over the similar endpoint, e.g., <https://medium.com/@kalishimthresearch/using-the-movie-database-api-to-analyze-streaming-services-9704f4b65de>, <https://www.youtube.com/watch?v=Z0HMX7f1Vw>.

To select candidate movies for the user study, an automated pipeline was developed to identify candidate films that exhibit a clear divergence between TMDb and colour-based recommendation logic. The system queries the TMDb API to retrieve a popularity-descending baseline of films, which were then cross-referenced against our local repository of numerical colour palettes. For each film, we computed the Earth Mover’s Distance (EMD) between the target and its top TMDb recommendations to identify the optimal colour-based match. We ensured that the two ‘distributions’ (colour palettes) have the same total mass (both are lists of colours with proportions adding to 1.0 or 100%). To ensure experimental validity, we filtered out cases where the TMDb and colour-based recommendations coincide. Furthermore, we required that palette similarity scores differ by a threshold of at least $T = 15 \Delta E$ units, to ensure that the selected colour-based recommendation is significantly more visually proximal to the target than the TMDb baseline, thereby creating a distinct contrast for participant evaluation. Finally, we made sure that the candidate and target titles did not match; otherwise, participants would be inclined to select a titular match as the best recommendation. We also omitted any movies for which recommendations are from the same series, because it makes the judgment trivial.

A trailer is generally 1.25 minutes, and three trailers take 3.75 minutes to watch. To reduce cognitive load and ensure the survey takes no more than fifteen minutes, we decided to include four trials. On March 20, 2026, we ran the [script](#) with a candidate colour difference threshold of 15, querying the first 50 pages returned by TMDb. We randomly shuffled the data using a reproducibility seed: `colourpalettes`. We configured the script to loop through the resulting batch until it found *five* suitable movies, in case any needed to be removed due to disturbing content. Survey data is shown in Table 2. Note that the dissimilarity score was computed with CEMD; a lower dissimilarity score indicates a closer match. Ultimately, we had to remove two movies (2 and 4) due to sensitive content (see footnotes) and re-run the script for the fourth movie. This time, we reversed the seed string, using the string `settelapruoloc`. The first movie resulting from this second run that was not already selected was *Limitless*.

To account for the dynamic nature of the TMDb `discover/movie` API endpoint (which is sorted by popularity), a temporal stability check was conducted on April 2 – two weeks after the initial data collection. Re-running the original query of the first fifty pages revealed an 83% retention (5 out of 6 movies) from the initial batch and 100% retention (4 out of 4 movies) of the movies actually used in the study. This high degree of consistency suggests that the sampling pool was not subject to significant short-term API volatility and that the selected stimuli remain representative of the mainstream cinematic landscape as defined by the platform’s ranking algorithms. The full list of the 50-page snapshot is archived for transparency [here](#).

The survey asks participants to watch the three YouTube videos for each movie and select the one they feel is the best recommendation based on ‘vibe’, or aesthetic resonance. We also added a third option in case one or more of the videos are unavailable in the participant’s country. There were 42 participants and 147 total selections. Our (colour-based) pick was selected 98 times (66.66%). TMDb’s pick was selected 49 times (33.33%). Performing a Chi-Squared Goodness

of Fit test, the result was $\chi^2(1) = 16.334, p = 0.000053$. There is a very strong statistically significant preference for our colour-based recommendations, with the likelihood of this distribution occurring by random chance roughly 1 in 18,800. This indicates that incorporating colour as a feature significantly improves user preference compared to standard collaborative filtering alone.

5 Future Work

Colour palettes can also be used as a feature to predict video memorability. We have worked with the researchers behind the [MediaEval](#) benchmarking initiative to incorporate our palettes as a video feature into the 2026 memorability task: ‘predicting the memorability of movie clips and commercial videos’. To this end, we generated image and numerical representations of Binned-KMeans colour palettes for 522 movie clips in the developer set and 134 movie clips in the test set. Teams of participating researchers are now charged with developing (machine learning) algorithms for measuring the memorability of these movie clips, which can use our palettes alongside any subset of visual, text, speech, audio, sensory, and other available features of their choosing. Results are slated for presentation at the MediaEval 2026 Workshop in June 2026.

Colour-based recommendations seem to be a desirable feature for users of streaming platforms. A significant contribution would be to suggest how an automated system might detect if a movie’s colour use is ‘notable’ – perhaps through high saturation variance or palette uniqueness – so that a streaming platform knows when to trigger this feature. Alternatively, users could opt in to this feature if *they* feel the colour used in the movie they just finished is notable.

6 Conclusion

Colour is an important tool used in filmmaking, and the very deliberate and strategic decisions thereof are usually a result of careful collaboration between directors, colourists, lighting crew, costume designers, makeup artists and more. In this paper, we present a literature review of research on colour-emotion association, as well as methods for colour palette generation and comparison. We also present the results of three user studies; the first evaluates an application prototype which makes colour palettes explainable and central in movie recommendation, the second confirms participants’ desire for the integration of colour in movie recommendation systems, and the third demonstrates that our colour can successfully improve TMDb movie recommendations.

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