From Hand Sketches to AI-Generated Cinematic Visualization Transforming Film Pre-production through Artificial Intelligence

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DOI: https://doi.org/10.47772/IJRISS.2026.102000019

Received: 15 October 2026; Accepted: 21 October 2026; Published: 19 November 2026

ABSTRACT

We know little about the impact of this transformation on film pre-production, despite the prospect of creating cinematic visual concepts from hand sketches and text prompts in mere moments with the help of generative AI tools like Midjourney, Stable Diffusion and Runway. This paper does not present empirical results, it is conceptual and methodological. It makes two contributions. First, it suggests a sequential, human-centred, 7-stage hybrid workflow for AI-supported pre-production visualisation that is rooted in the literature on human–AI co-creativity. Second, it outlines a convergent, mixed methods protocol for comparing that workflow with the traditional workflow of hand-sketch visualisation, which is pre-registrable: a within-subjects experiment with 30-40 film professionals, followed by operationalised rubrics-based blind expert evaluation and semi-structured interviews. The protocol specifies metrics for efficiency, iteration, visual quality, cinematic relevance, originality and creative control and establishes clear rules for the control of baseline drawing proficiency and prompt-engineering. From the existing studies seven hypotheses are proposed for testing. Issues of authorship, copyright, bias and professional displacement are explored with reference to the Indian context of cinema. The framework and design provide a replicable way for filmmakers, educators and researchers to question whether the use of AI for visualisation can enhance the decision-making process for filmmaking, or whether it simply speeds up image creation.

This course focuses on the application of AI in the film Pre-production workflow, particularly for storyboard creation, visualization, production design, and human–AI co-creativity in concept art and pre-visualization, with an emphasis on practical, hands-on examples. This course will be dedicated to the use of Artificial Intelligence in the film Pre-production workflow, specifically storyboard creation, visualization, production design and human–AI co-creativity in concept art and pre-visualization, with a focus on practical and hands-on examples.

INTRODUCTION

Film-making is a cooperative visual business. Filmmakers need to know how a screenplay will look on the screen and how it will look when it is applied to a set before cameras start rolling or sets are set up. Pre production or the preparatory stage involves script breakdown, research, location planning, production design, cinematographic planning, storyboarding, concept development, costume planning, scheduling and pre-visualisation. A lot of this involves visuals, as there are times when the audience needs help in understanding a concept when using just words would not be enough for a film maker.

Traditionally this process has been centred on hand-drawn sketches and story boards. Drawings are used by the directors and storyboard artists to plan camera positions, framing, composition, character movements and visual rhythm. Production Designers develop concept drawings and mood boards to communicate the style of

environment, props and architectural spaces. Cinematographers explain lighting, the use of lenses and camera movements through pictures. The use of visualisation has therefore been to a large extent dependent on the artistic skill, time and equipment of individual practitioners.

This was slowly transformed by the advent of digital imaging. Digital illustrations, 3D modelling, compositing and virtual production enabled visual concept creation and iteration to be much quicker than physical techniques. The next evolution is generative AI: concepts can be generated from natural language prompts and even reference images and sketches in an interactive way between the human and the machine. Multimodal and text-to-image systems like Midjourney, Stable Diffusion and DALL-E have demonstrated their ability to create complex images from brief descriptions, while multimodal and text-to-video systems are generalising to moving-image visualisation. In minutes, a filmmaker can explain a desolate railway station at night during the monsoon, shot on an anamorphic wide lens and lit by practical sodium-vapour lamps, and get several different translations for the picture.

It is particularly important for independent productions and budget-conscious films that do not have the luxury of time and resources for traditional concept art and storyboarding. A person who is not very good at drawing can communicate a visual concept by means of words, references, and create alternatives to discuss with others. Speed and convenience, however, doesn't mean better filmmaking. With generative systems, outputs are generated from statistical patterns that are learned from vast sets of data, and questions of originality, artistic agency and authorship arise. These findings from the high-level analysis of AI-generated art indicate improved productivity along with a decrease in average visual novelty (Zhou & Lee, 2024).

The human/AI co-creativity literature also warns against a human vs. AI creative dichotomy. For instance, Medeiros et al. (2025) suggest that, overall, there is no evidence that AI support helps human divergent thinking and conclude that, based on their findings, the quality of the AI support is important. This is directly applicable to pre-production. A filmmaker requires more than an attractive picture there has to be story, characters, continuity in space, camera logic, production feasibility, mood, and cinematic intention. It is not a question of whether AI can create beautiful images but how AI-powered visualisation enhances the quality of filmmaking decisions.

1.1 Aim, scope and contributions

This paper is of conceptual and methodological nature. It does not provide any reports of empirical findings that are finished. It is designed to (a) suggest a human-centred hybrid work process for film pre-production, with the integration of AI tools, and (b) outline a detailed and repeatable methodology for assessing the proposed workflow using a traditional hand-sketch visualisation system. Specifically, the paper:

Familiarizes oneself with literature relating to generative AI, creativity, digital storytelling and design practice, and pinpoints a gap that is specific to the film pre-production;

To apply the concepts of efficiency, visual quality, cinematic relevance, originality and creative control in explicit ways, using rating rubrics provided by experts; defines baseline drawing skills and prompt knowledge of the participants as design controls;

Makes testable inferences based on previous research and presents a framework of seven stages of Human-Centred AI Film Pre-production Model for subsequent empirical testing.

2. Background: The Pre-production of a Film with AI.

2.1 Traditional visualisation

The traditional film visualisation process starts with interpreting the screenplay. A storyboard artist works on a storyboard, which the director shows to them and they draw the shots to show the size of the shot, camera angle, etc. and where the characters are in the shot, if the camera is moving, etc. The production designer collaborates in parallel to design space for story, character and theme, using concept sketches, architectural references, colour

palette, material references and model making. Cinematographers need visual cues for lighting, framing and camera movement and lens attributes.

A storyboard is thus more than a drawing. It's an intermediate product used for negotiating the desired outcome of the departments. Pre-production visualisation is a collaborative process, not just a purely artistic process.

2.2 Digital transformation

The computer-based tools ushered in new ways of visualisation. Digital illustration meant that the artists were able to make changes to images without having to redraw them, three dimensional software meant that virtual environments and virtual cameras became possible, and digital pre-visualisation meant that scenes were simulated before production began. Since then, AI and computer vision have been used to storyboards. For example, Kerr, Haines and Li (2023) have created a system that automatically recommends a camera pose for unsupervised scouting and layout of films based on the analysis of the content on the screen. This trend of using AI to help with the creation of visual content continues with generative AI**.**

REVIEW OF LITERATURE

3.1 Generative AI and human creativity

The question of whether machines can be creative arose early. A better question today is about the interplay between human and AI systems in the creation of things. The results of the experimental evaluation of ChatGPT for ideation by Medeiros et al. (2025) showed that divergent thinking was not generally improved by using the AI, and that the quality and perceived quality of the support offered by the AI influenced the results. This undermines technologically deterministic views. In the cinematic world, AI can expand the possibilities for what kinds of shots to try, but it doesn't automatically mean the filmmaker will pick the most appropriate shot for the story.

3.2 Creative productivity

One of the most compelling benefits of using AI visualisation tools is their ability to boost productivity. The results on the users of text to image, however, indicate that increasing the output volume does not necessarily translate to a decrease in the average novelty (Zhou & Lee, 2024), meaning that productivity is not necessarily creative. The point is especially significant in film: the director may produce a hundred images per hour, but the significance of each one will rely on its relevance to the script, coherence as a sequence, narrative force and producibility.

3.3 Digital Storytelling and Collaborating

Wei et al. (2025) have compared a collaborative group using generative tools such as ChatGPT, Midjourney and Runway with a traditional group when working with a problem-solving task in digital storytelling. The AI-supported group showed enhancements in collaborative problem solving, some aspects of team creativity, but also raised the issue of over-reliance, cognitive offloading and emotional support. Pre-production is a collaborative storytelling process and these observations are directly relevant.

3.4 The practice of design and creative practice with AI.

Main (2024/2025) did a survey, diary studies and a digital-probe approach to get a sense of how creative professionals would like AI to help them. There was variation in preference according to task and three types of assistance were found: information support, generation support, and situational support. AI is not a one-size-fits-all solution for film research, as its application varies from location research and concept art to storyboarding and visual development.

3.5 Communication education and creative problem solving

Wang, Tian and Xie (2026) conducted a questionnaire with 768 students and interviews with 20 students about

Generative AI in Video Production. The findings showed that the use of AI was positively associated with learning motivation and career confidence, and interviews showed that there were tensions between efficiency/experimentation and standardisation/reduction of originality/dependency. The study location is educational, not professional, but the research findings suggest a combination of quantitative measures and interviews.

Experimental results on ideation are mixed. Lin and Xie (2026) conducted a mixed-methods experiment on the comparative analysis of traditional, internet-assisted and GenAI-assisted design ideation, which focused on both the production of designs and the participants' experiences. In related work, it is reported that AI support did not consistently decrease fluency, flexibility or originality but that semantic divergence was less when using AI support and that ideas generated with AI support were more similar to existing products. These findings together suggest a consideration of the two perspectives in tandem.

4. Research Gap

While there are many studies on the role of generative AI for creativity and design and digital storytelling, there are five gaps.

1. The studies mostly focus on AI-generated art or the ideation process of creativity in general rather than on the film pre-production process.

2. Very few empirical studies directly compare traditional hand-based visualisation with AI-supported cinematic visualisation with the same narrative stimulus.

3. Research tends to focus on either perception or productivity, and rarely integrates workflow performance, visual quality and professional experience.

4. While the roles of the director, cinematographer, production designer and storyboard artist are under-studied, the role of specific filmmaking actors has not been studied.

5. While much of the discussion of creative control and authorship and professional identity, so far, has been theoretical, they have rarely been investigated empirically in the field of film.

The protocol outlined here aims to meet these needs in a comparative mixed-methods approach

5. Problem statement and research questions

As the use of generative AI expands, how ideas are rendered in movies is evolving. While traditional pre-production involves several iterations of drawing skills and manual production, AI systems can rapidly yield multiple drafts of visual ideas in seconds. Whether faster generation translates to better final film decisions, if AI limits originality, how much control will filmmakers have, and whether AI-generated images will be more suitable for cinematic purposes than hand-drawn images remain unclear.We don't know whether quicker generation is better at film decisions, if AI limits originality, how much control will filmmakers have, or whether AI-generated images are better suited for film than hand-drawn images. The study thus addresses the question of whether the transition from hand sketches to AI-produced visualisation impacts efficiency, visual quality, creative control, collaboration and professional practice in pre-production.

The following goals are used to guide the work:

1. To compare traditional hand-sketch and AI assisted workflows in Film pre-production visualisation.

2. To create a contrast in the time needed to develop film visual ideas.

3. To evaluate the difference in visual quality, cinematic relevance and originality compared to the screenplay.

4. To explore how AI affects creative control and artistic decision-making.
5. To learn about the experience of filmmakers with AI-enabled collaboration.
6. Recognise ethical, copyright and authorship challenges related to AI-produced visualisation.
7. Development and improvement of a Responsible Human – AI hybrid model for film pre-production.

6. Methodological Basis in prior research

A convergent mixed methods approach is used in the design. Qualitative methods capture how the filmmakers interpret the AI assistance, negotiate creative control, and decide to accept or reject AI-generated concepts, while the quantitative methods capture production time, iteration counts, expert ratings and between workflow differences. There is a strong emphasis in mixed-methods scholarship that both lines of inquiry need to be combined and not reported separately. Fetters, Curry and Creswell (2013) outline the processes of connecting, building, merging and embedding in relation to integration, and Venkatesh, Brown and Bala (2013) note the importance of meta-inferences based on integrated evidence. Specific design choices are informed by six recent studies (Table 1).

Table 1. The proposed design is based on previous research.The design has been informed by previous research.

Study	Design	Element adopted here
Medeiros et al. (2025)	Experimental design with a creativity measure; AI vs. no-AI ideation	Controlled comparison of AI-supported and conventional visualisation
Wei et al. (2025)	Pre/post measurement with semi-structured interviews	Interviews on collaboration and creative experience combined with quantitative evaluation
Wang et al. (2026)	Survey (n = 768) and interviews (n = 20)	Structured questionnaire plus qualitative interviews
Lin and Xie (2026)	Mixed-methods experiment: unaided, internet-assisted, GenAI-assisted ideation	Direct comparison of alternative visualisation conditions
Cavallin and Spagnol (2026)	Pre/post questionnaires, behavioural observation and interaction tracking with professional designers	Recording workflow behaviour, iteration counts and interaction patterns
Main (2024/2025)	Survey, diary and digital-probe study of creative professionals	Identifying which pre-production tasks professionals wish to delegate to AI

7. Proposed Research Design

The study is conducted in three phases: (I) a within-subjects comparative visualisation experiment, (II) blind expert evaluation of the visual outputs and (III) semi structured interviews. The quantitative strand is produced in Phases I and II, while the qualitative strand is produced in Phase III. The strands are gathered together and combined at the interpretation level.

7.1 Phase-I comparative visualisation experiment

Participants are required to do two visualisation tasks, one in Condition A (traditional hand-sketch workflow) and one in Condition B (AI-assisted workflow) with the same text-to-image tool and model version, where sketch and reference-image input is allowed. In both cases, the resulting deliverable will be a fixed set of 6 key frames chosen from the script extract and will fully represent the following: establishing shot, character introduction, interior/exterior environment, camera angle, lighting, mood, spatial relationships and character positioning. It's not about finding the prettier image, it's about finding the workflow that works for moving an image towards a cinematic decision.

Two similar script extracts (Scene X and Scene Y) are matched in terms of length, number of characters, setting complexity and lighting requirements to avoid any difficulty and practice effects that could be confused with workflow effects. The participants are randomly assigned to one of four sequences within a 2 × 2 counterbalanced design (A-then-B or B-then-A, crossed with Scene X first or Scene Y first).They are randomly assigned to one of four sequences (A-then-B, or B-then-A, and Scene X first, or Scene Y first) in a 2 × 2 counterbalanced design. Comparable opportunity is provided by a time cap per condition, to be calibrated in a pilot and by keeping screen recording and prompt logs to capture the time and interaction on the workflow.

7.2 Participants and sampling

Purposive sampling is used because a special knowledge about the production of films is required.

- **Professional Participants (n ≈ 30-40):** directors, cinematographers, production designers, storyboard artists, concept artists, assistant directors and visual development artists. A within-subjects comparison is assumed to be done to a medium standardized effect (d = 0.5), α = .05 (two-tailed) and with a power of .80, which means 34 participants should be recruited for the final study; this number will be verified after pilot data and ethics approval.

- **Independent expert evaluation panel (n ≈ 8–12):** Professional film makers who were not involved in Phase I and provide ratings independently.

- **Interview subsample (n ≈ 15-20):** Selected from the Phase I participants with maximum variation in role and baseline skill.

Final sample sizes will be determined based on accessibility, statistical power and institutional ethics approval, and will be given after data collection.

7.3 Controlling baseline skill and other confounds

Participants vary in their ability to draw and their ability to prompt the drawing activity, both of which might cause differences in time and quality of the drawing when compared. A prompt-experienced participant may prefer Condition B, for instance, while a skilled illustrator might prefer to be fast but may draw poorly. The protocol thus assesses trait skills at pre-test, and adjusts for pre-test level in design and analysis.

Table 2. Confounding factors need to be identified, as does the plan for controls.

Confound	Risk	Control
Drawing proficiency	Advantage in Condition A; inflates hand-sketch speed and quality	Baseline Drawing Task (15 min; standard reference description; two independent raters score composition, perspective and expressive clarity, 1–5), plus years of professional drawing practice; z-scored and entered as covariate and moderator
Prompt-engineering proficiency	Advantage in Condition B	Baseline Prompting Task (15 min; participant must reproduce a target image from its description; rated for fidelity to target, 1–5), plus self-reported weekly AI-tool use; z-scored and entered as covariate and moderator
Tool familiarity	Unequal experience with the chosen AI tool	Same tool, model version and settings for all; standardised 45-minute onboarding for all participants before Condition B

Confound	Risk	Control
Allocation of skill across orders	Skilled participants clustering in one condition order	Stratified block randomisation to the four sequences using skill tertiles from the baseline tasks
Professional role	Directors and artists may differ in drawing and prompting ability	Role recorded and tested as a covariate; subgroup results reported descriptively
Order, practice and scene effects	Learning from first task; unequal scene difficulty	2 × 2 counterbalancing; matched scenes; order and scene entered in the model
Rater bias from medium cues	Raters can often tell a sketch from an AI image	Standardised digitisation; separate rating passes (see Section 7.4); raters' guesses about medium recorded; raters blind to participant identity and baseline scores
Fatigue and time pressure	Second task suffers	Fixed breaks; time cap per condition; tasks on separate sessions where feasible

Between-person skill differences are already absorbed in part because each participant is his or her own control. Skill is also considered a moderator variable, allowing the analysis to demonstrate the extent to which AI assistance is beneficial for specific groups (e.g., whether it helps the weaker drawers at least catch up with the stronger drawers).

7.4 Measures and operational definitions.

Where possible, workflow metrics are automatically recorded. The total time of the workflow is from the receipt of the script extract to the submission of the finished key frames and is divided into ideation, generation or drawing, selection, and refinement, therefore prompt development, selection and correction and post generation refinement are included in the Condition B, and not only image generation time is counted. Iteration metrics consist of the number of different images created, the number of these images that are kept for the final set, and the "retention ratio". Behavioural measures of control are the percentage of the images held on the hand that are altered and the number of times the images are prompted.

Table 3. Operational definitions and rating rubric

Construct	Operational definition	Anchors (rated 1–5)
Visual quality	Technical and aesthetic execution of a frame: clarity, compositional balance, coherence of rendering, absence of visible artefacts or distortions	1 = unclear or visibly flawed; 3 = competent; 5 = polished and fully coherent
Cinematic relevance	Extent to which a frame communicates shot-level information (shot size, camera angle, framing, depth and lens cues) usable by the cinematographer	1 = no usable camera information; 3 = partly usable; 5 = directly usable as a shooting reference
Narrative alignment	Fidelity to the script extract: setting, character action, story moment and intended mood	1 = contradicts script; 3 = partly faithful; 5 = fully faithful and story-bearing

Construct	Operational definition	Anchors (rated 1–5)
Spatial continuity	Consistency of geography, character positions, screen direction and scale across the six-frame set	1 = contradictory; 3 = minor inconsistencies; 5 = fully consistent
Lighting logic	Plausibility and motivation of light source, direction, quality and time-of-day cues, and consistency with intended mood	1 = implausible; 3 = plausible but unmotivated; 5 = motivated and mood-supporting
Production feasibility	Whether the frame could be realised with the stated set, location and budget tier	1 = not achievable; 3 = achievable with major compromise; 5 = readily achievable
Cultural accuracy	Faithfulness to the culture and setting specified in the script; absence of stereotyped or inaccurate representation	1 = stereotyped or inaccurate; 3 = generic; 5 = specific and accurate
Originality	Novelty and appropriateness of the visual treatment relative to the other outputs and to conventional treatments of the scene (consensual assessment)	1 = entirely conventional; 3 = some fresh elements; 5 = distinctive and fitting
Perceived creative control (participant self-report)	Participant's sense of directing the visual outcome, measured after each condition with a short 7-point Likert scale with two subscales: concept-level control ("the final frames reflect my intended vision") and detail-level control ("I could determine specific visual details")	1 = strongly disagree; 7 = strongly agree; reliability (Cronbach's α) reported after piloting

7.5 Phase III: Qualitative interviews

The topics discussed in semi-structured interviews are as follows:

1. Experience of past tradition of visualisation;
2. Experience of AI generated visualisation;
3. A feeling of creative control;
4. The impact of AI on creative decision making;
5. collaboration between departments;
6. Have confidence in AI-generated images;
7. concerns about originality;
8. copyright and authorship;
9. professional displacement; and
10. preferred human–AI workflow.

Interviews are audio recorded, transcribed and analysed using reflexive thematic analysis and then double coded by a second coder to verify coding consistency for a sample of transcripts.

7.6 Data analysis and integration

Primary outcomes are set up in advance to reduce multiplicity: total workflow time, composite of cinematic relevance, narrative alignment and spatial continuity, and perceived creative control. All other measures are secondary or exploratory. Two linear mixed-effects models are used to analyse each outcome, with condition, order, scene, z-scored drawing skill, z-scored prompting skill and interaction between condition and skill as fixed effects and random intercepts for participant (and for rater in the rating outcomes). Bootstrapped and rank-based alternatives to distributional assumptions are used where distributional assumptions fail. Reported are the effect size with 95% confidence intervals (CIs), Holm corrected across main outcomes. Sensitivity analyses are repeated models, but with exclusion of participants in the extremes of skill.

Qualitative themes are combined with quantitative results in joint displays as one aspect of the assessment of ratings of creative control can be seen alongside one's interview account of the same. Convergence, divergence and complementarity between the strands are then interpreted as meta- inferences (Fetters et al., 2013; Venkatesh et al., 2013). Study plan, hypotheses and analysis scripts should be open registered ahead of data collection.

7.7 Research ethics

Ethics approval from institutions and informed consent must be obtained. Participants are informed of the recording of their screen activity and prompts; data is anonymised and stored securely; participants are given compensation for their time; and the terms of use of the AI tool are considered and the study does not infringe on these terms. Study prompts do not identify living artists nor do they depict trademarked characters, and ownership of outputs produced during the experiment is agreed upon in advance with participants.

8. Hypotheses and Analytical Framework

Below are the hypotheses derived from the literature reviewed above that will be tested rather than assumed. These are all expressed in advance of collecting data with the test for each (Table 4). Hypotheses H3–H5 make deliberate assumptions that the more images generated the faster, and the more images generated the better, the better does not necessarily mean the more original or the more cinematic.

Table 4. Hypotheses, rationale and test measures

No.	Hypothesis	Basis in literature	Primary measure
H1	Total workflow time (including prompt development, selection and refinement) is shorter in Condition B than in Condition A.	Productivity gains with text-to-image tools (Zhou & Lee, 2024)	Total workflow time (recorded)
H2	Condition B yields more distinct visual alternatives, but time to final decision per alternative is not shorter than in Condition A; more alternatives may mean selection overload.	Concerns about dependency and convergence (Wang et al., 2026; Lin & Xie, 2026)	Images generated; retention ratio; decision time
H3	Condition B receives higher ratings for visual quality.	Capacity of current tools to render lighting and environment	Visual quality rating

No.	Hypothesis	Basis in literature	Primary measure
H4	Condition B does not receive higher ratings than Condition A for cinematic relevance, narrative alignment and spatial continuity (tested two-sided; hand sketches may be equal or superior).	Quality of AI support shapes outcomes (Medeiros et al., 2025)	Cinematic relevance, narrative alignment, spatial continuity ratings
H5	Condition B outputs are not rated as more original, and outputs are more similar to each other across participants than in Condition A.	Lower average novelty and semantic divergence under AI (Zhou & Lee, 2024; Lin & Xie, 2026)	Originality rating; between-participant similarity rating
H6	Perceived concept-level control is equal or higher in Condition B, while perceived detail-level control is lower.	Shift from creative execution to creative direction	Creative control subscales
H7	Baseline drawing and prompting skill moderate the condition effect on primary outcomes.	Dependence of AI output quality on user skill	Condition × skill interactions

There are no directional hypotheses for the following exploratory qualitative questions: Collaboration, authorship, trust, cultural representation, and professional identity. One requirement is noted for examination: Although shared AI-generated images can facilitate inter-departmental communication by creating a common visual object, they can also cause the experts to consider an image as a prototype instead of a reference, which can result in prematurely settling on one interpretation.

9. Ethical, Legal and Professional Issues

9.1 Authorship

Traditional conceptions of authorship are complicated by AI. In the case that an image is generated by a filmmaker's prompt, a reference image, model training data and algorithmic synthesis, it is difficult to identify what portion the prompt, the reference image, the model training data and the algorithmic synthesis contributed to the generation of the image. The authorship debate surrounding the advent of generative AI (Haidemariam, 2026) indicates that this is a viable minimum standard for crediting and attributing creative decisions: provenance records including prompt logs, version of models and human edits.

9.2 Copyright

The training data can be very vast sets of existing images, posing questions for the relationship between training data, generated images, and copyright. Mazzi (2024) states that there is uncertainty regarding originality and prompting and the ownership of AI generated works. The roles in the law vary from one jurisdiction to another and are continually changing.

9.3 Bias and cultural representation

This can be gender, race, geographical, architectural, clothing and ornamentation, all of which can be reflected in the culture and representational bias in the models' training data. This is important for Indian filmmaking: prompts that mention Indian communities, places or cultures might produce stereotypical or inaccurate images and therefore, cultural accuracy is a rated construct in the protocol.

9.4 Professional displacement

There could be a decline in demand for repetitive visual production and an increase in demand for new skills like assistive technology in direction, prompt and visual evaluation. Technological change is therefore not considered as complete replacement or complete preservation, but as a change in occupations.

10. A Proposed Human-Centred AI Film Pre-production Model.

Based on literature and the proposed workflow, we proposed the following seven stage hybrid workflow (Table 5) where the human sets intention and makes final judgement, while AI is utilized for rapid exploration. The model is conceptual and will be judged based on the protocol above and then by practitioners through subsequent validation.

Table 5. The focus is on the users' needs and requirements. Seven-stage Human-Centred AI Film Pre-production Model focuses on the needs and requirements of the user.

Stage	Activities and roles	Output / decision gate
1. Human concept development	Director and creative team establish narrative intention, character motivation, visual tone, cultural context and cinematic style	Creative brief that precedes any AI use
2. Hand sketching	Rough sketches for quick visualisation and direct human engagement with composition, preserving the human factor	Human-authored thumbnail set
3. AI exploration	AI generates alternative environments, compositions, lighting concepts, costumes, props and visual moods from prompts, sketches and references	Candidate image pool with prompt and model log
4. Human evaluation	Team assesses candidates for narrative relevance, originality, feasibility, cultural appropriateness and continuity (using the Table 3 criteria)	Shortlist with recorded rationale
5. Human refinement	Selected output is edited, redrawn or composited by the team	Refined frames with documented human contribution
6. Departmental communication	References shared with the director, cinematographer, production designer, storyboard artist, VFX team and art department, labelled as references rather than prototypes	Shared visual reference pack
7. Production translation	Approved visualisation guides, but does not replace, professional decision-making in production	Approved guidance feeding shooting and art-department plans

11. Contributions

11.1 Theoretical contribution

The paper is an extension of the literature on human–AI co-creativity in three ways. It shifts the conversation from the AI creativity to the real-world context of filmmaking, shifts the focus from image generation to co-creative visualization and connects the technological effectiveness with the creative agency. It also calls into question two counterfeit views: technological determinism that advances the idea that AI will lead to more creativity, and technological replacement that suggests that AI will replace creative jobs. The framework, on the other hand, sees outcomes as the result of technology, human knowledge, task and evaluation.

11.2 Practical contribution

Filmmakers can figure out that AI is useful in enhancing productivity or not.

AI can help accelerate environment and concept development, which can be assessed by production designers.

AI-generated composition and light references can be tested for their utility by cinematographers.Cinematographers can experiment with the usefulness of AI-generated composition and lighting references.

Directors can review and evaluate the communication of their vision from AI to the rest of the team.

Film teachers can create lesson plans to integrate visual and AI literacy.

Independent filmmakers can evaluate for themselves whether their visual development is more economical using hybrid workflows.

12. Limitations

1. The protocol and framework are presented in this paper, but there are no experimental results reported and the proposed hypotheses are yet to be tested.

2. The results generated by AI systems are constantly changing, so results from one version of the model may not apply to other versions. The tool and version must be reported as it is.

3. The quality of the output will depend on the knowledge of the user and his or her prompting capacity; this can be measured and is controlled by the protocol, but it can not be eliminated.

4. Even if there are reliable checklists and rubrics for assessing visual creativity, there is considerable subjectivity involved.

5. The professional sample will probably be small, and purposefully selected, which will restrict generalisability.

6. The study only focuses on pre-production visualisation and is not a representation of the whole process of filmmaking.

7. Raters can seldom be fully blind to the medium, despite standardised presentation.

8. The law about copyright and authorship is different in various countries, and is still developing.

CONCLUSION

AI is changing film pre-production visualisation. An old, familiar path between screenplay and hand sketch is now supplemented by a new one, leading from textual or visual ideas to cinematic references in minutes. But it's

not just about the speed: generative AI also alters the way filmmakers experiment and consider a broader range of visual concepts, enables rapid iteration of ideas and disseminates them among departments.

While greater productivity can signify greater creativity, this is not a foregone conclusion. Previous research indicates lower average novelty and convergence effects in some contexts, as well as AI support that can be helpful or problematic depending on the quality of the AI and individuals' use of it. However, the main issue is not whether AI can replace the traditional visualisation, but how it can be integrated in a way that doesn't take the place of the human processes that make cinema culturally, emotionally and artistically special.

This paper has provided the Human-Centred AI Film Pre-production Model and the protocol with the operational measures for testing the model, which has been conducted in a controlled way and with a mixed method. There are plans for an immediate pilot study involving the calibration of time caps, rubrics and rater reliability, pre-registration, and a full within-subjects study with professional filmmakers. The hybrid model would mean that the filmmakers would carry out the task of interpreting the story, making aesthetic judgments, being culturally sensitive and being the author to make the final creative decisions, while the AI handles the immediate process of visual exploration and iteration. Whatever happens, human imagination will play a role in the future of film pre-production, combined with some exploration by algorithms and human judgment.

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