

Understanding Creative Potential and Use Cases of AI-Generated Environments for Virtual Film Productions: Insights from Industry Professionals

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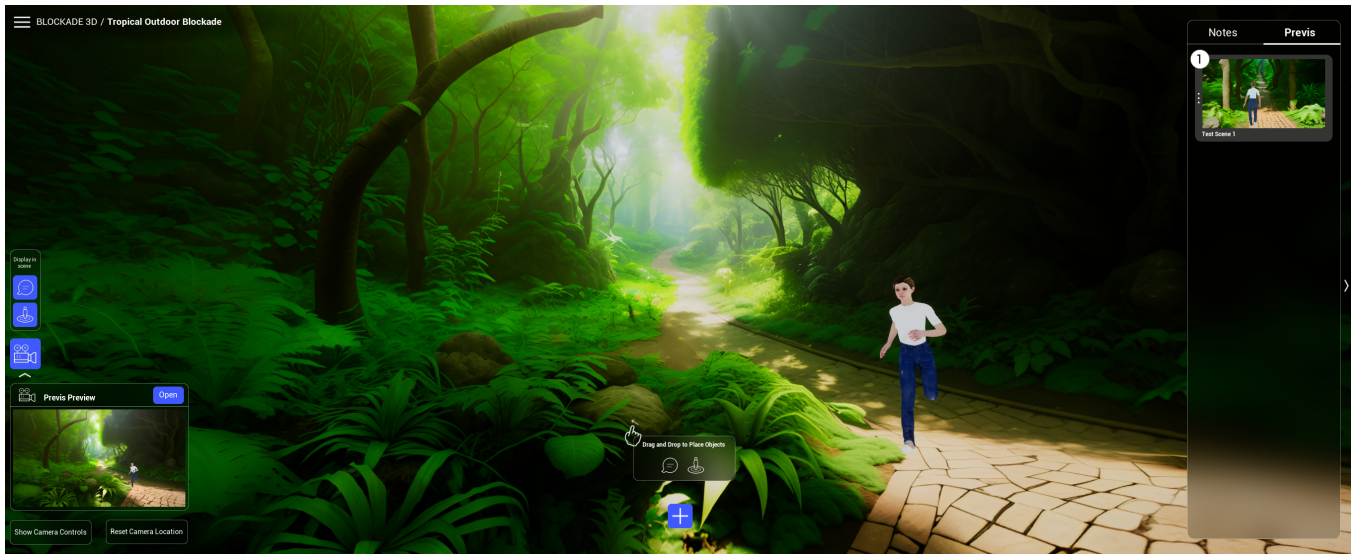


Figure 1: *EnVisualAIzer* Prototype User Interface for Exploring AI-Generated Environments, showing Previs Camera, Character and Note Placement Options, and Saved Scenes.

Abstract

Virtual production (VP) is transforming filmmaking by integrating real-time digital elements with live-action footage, offering new creative possibilities and streamlined workflows. While industry experts recognize AI's potential to revolutionize VP, its practical applications and value across different production phases and user groups remain underexplored. Building on initial research into generative and data-driven approaches, this paper presents the first systematic pilot study evaluating three types of AI-generated 3D environments—Depth Mesh, 360° Panoramic Meshes, and Gaussian

Splatting—through the participation of 15 filmmaking professionals from diverse roles. Unlike commonly used 2D AI-generated visuals, our approach introduces navigable 3D environments that offer greater control and flexibility, aligning more closely with established VP workflows. Through expert interviews and literature research, we developed evaluation criteria to assess their usefulness beyond concept development, extending to previsualization, scene exploration, and interdisciplinary collaboration. Our findings indicate that different environments cater to distinct production needs, from early ideation to detailed visualization. Gaussian Splatting proved effective for high-fidelity previsualization, while 360° Panoramic Meshes excelled in rapid concept ideation. Despite their promise, challenges such as limited interactivity and customization highlight areas for improvement. Our prototype, *EnVisualAIzer*, built in Unreal Engine 5, provides an accessible platform for diverse filmmakers to engage with AI-generated environments, fostering a more inclusive production process. By lowering technical barriers, these environments have the potential to make advanced VP tools more widely available. This study offers valuable insights into the

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evolving role of AI in VP and sets the stage for future research and development.

CCS Concepts

• **Human-centered computing** → HCI design and evaluation methods; Empirical studies in HCI; Graphical user interfaces; • **Computing methodologies** → Reconstruction; Computer graphics; • **Applied computing** → Media arts; • **Information systems** → Multimedia content creation.

Keywords

Virtual Production (VP), AI-Generated 3D Environments, Filmmaking Workflows, 3D Scene Reconstruction, Gaussian Splatting, Generative AI, Previsualization, Interactive Media, Real-Time Rendering, Human-Computer Interaction (HCI), Creative Collaboration, Graphical User Interface (GUI), Immersive Storytelling, Digital Content Creation.

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1 Introduction

"If you're trying to use virtual production as a tool to empower fewer people to do more amazing things, then let's start removing all of these unnecessary complications, and we can do that with AI. So you can walk into an empty room and say, 'Give me a 1940s-era Western frontier town, and oh, let's make it winter.'"

– Ben Grossmann, Virtual Art Department, 2019 [24]

Ben Grossmann's vision in 2019 highlights AI's transformative impact on Virtual Production (VP). His foresight into its potential for setting scenes and sets, even before the public release of tools and models like Midjourney¹ or Stable Diffusion [43], underscores the significant role these technologies could play in reshaping creative workflows by simplifying the creation of and interaction with complex virtual environments.

Virtual Production merges real-time computer-generated content with live-action footage, as demonstrated in projects like *The Mandalorian*². VP has transformed traditional filmmaking by enhancing creative flexibility, efficiency, and collaboration across teams. By integrating digital environments during production, filmmakers can visualize complex scenes in real-time, reshaping how ideas are developed and communicated [23, 24].

Recent advancements in AI-generated environments, such as Neural Radiance Fields (NeRFs) [35], 3D Gaussian Splatting (3DGS) [25],

and 360° panorama generation like Blockade³, could potentially amplify VP capabilities by enabling filmmakers to create immersive, adaptive environments that streamline workflows, particularly in early-stage production. We hypothesize that these technologies may reduce the need for extensive resources, making VP more accessible to smaller teams and independent filmmakers. While these tools reduce the need for VFX expertise, their technical complexity might still be a barrier to broader adoption. Increasing their accessibility could democratize VP, allowing more filmmakers to experiment and collaborate without requiring deep technical knowledge.

AI and game engines, such as Unreal Engine, have been used in filmmaking, but often in isolation and with distinct limitations: AI tools often operate within two-dimensional parameters with limited control, while game engines provide interactivity but are technically demanding. Our research combines the strengths of both, using 3D AI-generated environments that offer greater control and versatility while reducing technical challenges in a custom built prototype.

Our research explores the creative potential of various AI-generated environments in VP for more filmmakers, not just VFX experts. Using the *EnVisualAIzer* prototype, built in Unreal Engine 5 (UE5), we made AI-generated environments—Depth Mesh [50], 360° Panoramic Meshes, and Gaussian Splatting—easily explorable and assessable. These methods were chosen for their diverse approaches, encompassing both generative techniques and scene reconstruction, as well as their seamless integration into UE5. Our goal was to evaluate the applicability of AI-generated environments in real-world filmmaking workflows, focusing on previsualization, ideation, and their overall utility. Through a pilot study with 15 filmmakers, we refined evaluation criteria grounded in expert input to assess the effectiveness of these environments and analyze their use cases in various production stages.

Our findings suggest that different environments excel at different early production phases and concept development: Gaussian Splatting was most effective for detailed previsualization, while 360° Panoramic Meshes and Depth Mesh were more suited to early-stage ideation. Limitations such as restricted interactivity and customization indicate areas for improvement in future AI tools.

Our contributions include:

- **Empirical insights:** Data on how filmmakers use AI-generated environments in creative workflows.
- **Evaluation criteria:** A framework for assessing the creative potential of AI environments, refined through expert and participant feedback.
- **Use case differentiation:** Identification of how different AI environments support specific stages of production, from ideation to previsualization.
- **Design implications:** Insights into usability challenges and technical constraints, guiding the development of accessible AI tools for creative industries.

¹Midjourney. Image Generation Tool. Available at <https://www.midjourney.com>

²The Mandalorian. TV Series(2019-today). IMDb <https://www.imdb.com/title/tt8111088/>

³Blockade Labs. 360° panorama generation. Available at <https://www.blockadelabs.com>

2 Related Work

2.1 Virtual Production

Film production traditionally follows a linear process, moving through stages like pre-production, production, and post-production, with limited opportunities for adjustments once filming begins [39]. VP disrupts this model with various new concepts, allowing filmmakers to make creative decisions throughout the process. Its key advantage lies in enabling real-time collaboration across departments, fostering iterative creativity previously constrained to post-production. Techniques such as live green screen replacement or In-Camera Visual Effects (ICVFX), led by Epic Games' Unreal Engine⁴, allow for the real-time visualization of virtual environments, enabling on-set adjustments to lighting, set design, and camera angles. LED walls or volumes can additionally minimize the need for green screens, reduce post-production, and provide natural atmospheric effects [23, 24, 42]. VP also comprises concepts like Previsualization (Previs) for experimenting with camera angles and lighting, as well as Techvis and Stuntvis for pre-planning complex movements and stunts. Performance Capture blends characters' live-action movements with digital elements, while ICVFX allows final-pixel imagery to be captured during filming [24].

The rising importance of VP is reflected in its increasing adoption and growing market forecasts [18]. Experts predict AI integration, particularly 3D Gaussian Splatting (3DGS), will drive future trends in VP by simplifying workflows [18, 21, 48]. Though 3DGS still requires adaptation, it offers a valuable opportunity for future research to refine its application in VP.

2.2 AI-Generated Environments

AI-generated environments rely on two main approaches and hybrid forms: generative and data-driven methods [44, 59].

Generative methods synthesize 3D scenes from scratch using models like Generative Adversarial Networks (GANs) and diffusion models. While much of the focus has been on object generation [28, 37, 38], recent efforts are shifting toward generating entire 3D environments. *Taming Stable Diffusion* [62], for instance, generates 360° panoramic environments from text prompts, creating cohesive, high-quality virtual spaces. Similarly, *SceneScape* [15] focuses on generating 3D environments by building long-term videos with consistent geometry and realistic parallax effects as the camera moves through the scene.

Data-driven methods, including *Neural Radiance Fields (NeRFs)* [35] and *3D Gaussian Splatting (3DGS)* [25], reconstruct 3D environments from 2D images or depth data. NeRFs generate photorealistic 3D views by optimizing a neural network to model the volumetric scene representation, synthesizing novel views from 2D images, and handling complex lighting effects like reflections and transparency. 3DGS, on the other hand, accelerates rendering by representing scenes using thousands of tiny Gaussian functions that efficiently

model surface detail and lighting, making it ideal for interactive environments, where speed and quality are critical. Unlike traditional methods such as photogrammetry and Structure from Motion (SfM), which rely on feature matching and manual calibration, these AI-driven approaches leverage deep learning to achieve higher automation and adaptability, offering a more efficient workflow with fewer constraints on data acquisition [9, 63].

Hybrid approaches combine both methods for flexibility and efficiency. Techniques like *Pix2NeRF* [7], which generates NeRFs from a single image, and *LDM3D* [46], which merges latent diffusion with depth mapping for 360° views, illustrate this integration. AI-assisted tools like *NVIDIA Omniverse*⁵ and integrations for Blender⁶ automate tasks such as texture generation and model stylization, streamlining 3D workflows and supporting real-time collaboration [22].

2.3 AI-Generated Environments in Virtual Production

Academic research on AI in virtual production is still extremely rare. Song et al.'s [45] work stands out as the only one to explore generative and data-driven techniques for enhancing cinematic experiences. They categorize AI methods into HDR image-based scene creation, generative models (e.g., GANs and VAEs), and 3D model construction via point clouds and fractal modeling. Their study demonstrates the use of text-to-image generation for LED-wall virtual production, using HDR images to create high-quality environments. They focus on a single scene type and do not include extensive qualitative and no quantitative analysis [45].

Community-driven research from content creators provides practical insights into AI's application in VP. Artists like Mick Mahler (Mickmumpitz) [34] have integrated Stable Diffusion and Blender to generate 3D environments from text prompts and depth maps [32, 33, 50]. Creators like Bad Decisions Studios [49] also prototype virtual environments using NeRFs and 3DGS in Unreal Engine, showcasing the practical potential of AI technology [47]. These experiments offer immediate feedback on the usability, limitations, and creative possibilities of AI tools, complementing academic research by providing real-world insights from those adopting AI in filmmaking.

2.4 Related Tools

Several commercial software tools support different stages of film production, serving as valuable references for developing AI-generated environments. These tools enhance the filmmaking process by offering features for collaboration, real-time feedback, and content visualization across media review, virtual scouting, and previsualization tasks (see Table 1). However, as proprietary industry solutions, they currently lack standardized studies or benchmarking methods to comprehensively evaluate their impact on production workflows. Additionally, these tools are often specialized for specific tasks and do not provide comprehensive support for working

⁴Unreal Engine. Game Engine. Available at <https://www.unrealengine.com>

⁵NVIDIA Omniverse. Collaboration platform. Available at <https://developer.nvidia.com/omniverse>

⁶Blender. 3D software. Available at <https://www.blender.org>

with various AI-generated environments. This study aims to address these gaps by identifying and integrating key features from existing tools into a unified solution that facilitates interaction with different types of AI environments, offering a more versatile and adaptable approach to virtual production.

Media review tools like *CineSync*⁷, *FTrack Review*⁸, and *SyncSketch*⁹ enable remote collaboration and detailed feedback. *CineSync* offers synchronized playback with frame-accurate annotations for scene reviews, while *FTrack Review* integrates task management and version tracking. *SyncSketch* supports real-time and asynchronous feedback for 3D models and videos, making it adaptable for AI-generated environments.

For virtual scouting and previsualization, tools like *Unreal Engine Virtual Scouting*¹⁰, *Unity Reflect*¹¹, and *Google Earth Studio*¹² allow filmmakers to explore virtual environments in real-time. *CineTracer*¹³ offers real-time cinematography simulation, and *Matterport's*¹⁴ **3D scanning** captures real-world spaces for virtual scouting and set design.

Real-Time VP and AR Tracking tools like *CamTrackAR*¹⁵, *SkyGlass*¹⁶, and *Lightcraft Jetset*¹⁷ offer accessible solutions for integrating virtual elements into live-action footage on a smartphone. These tools utilize AR and AI-assisted tracking and keying to provide real-time visualization, allowing filmmakers to roughly align imported 3D digital environments with physical scenes. However, they remain primarily suited for independent creators and small-scale productions due to limitations in tracking precision, hardware dependency, and real-time rendering quality. Skyglass particularly stands out, by already providing AI skybox generation and Gaussian Splatting support.

3 User-Centered Design Approach

3.1 Preliminary Expert Interviews

To align the development of AI-generated environments with practical industry needs, we conducted user-centered informal interviews with five film professionals, including a VFX supervisor (P1), a post-production supervisor (P2), a cinematographer (P3), a virtual production technician (P4), and a NeRF expert (P5).

⁷CineSync. Remote collaboration tool. Available at <https://www.cinesync.com/>

⁸FTrack Review. Media review and task management. Available at <https://www.ftrack.com/en/review>

⁹SyncSketch. Real-time feedback tool for 3D models and videos. Available at <https://www.syncsketch.com/>

¹⁰Unreal Engine Virtual Scouting. Available at <https://www.unrealengine.com/en-US/virtual-production>

¹¹Unity Reflect. AR/VR collaboration tool. Available at <https://unity.com/products/unity-reflect>

¹²Google Earth Studio. 3D geographic visualization. Available at <https://www.google.com/earth/studio/>

¹³CineTracer. Cinematography simulation tool. Available at <https://www.cinetracer.tv/>

¹⁴Matterport. 3D scanning and virtual tours. Available at <https://matterport.com/>

¹⁵CamTrackAR. Real-time camera tracking app. Available at <https://www.camtrackar.com/>

¹⁶SkyGlass. AR virtual production tool. Available at <https://www.skyglass.com/>

¹⁷Lightcraft Jetset. Virtual production compositing tool. Available at <https://www.lightcrafttech.com/>

Interview Focus: The 30-60 minute long semi-structured interviews gathered feedback on the challenges and potential applications of integrating AI-generated environments into workflows. The detailed list of interview questions can be found in Appendix A. The participants were shown examples of AI-generated environments to ground their feedback in real-world use cases. Interview questions targeted areas such as previsualization, dynamic scene integration, and ease of use for non-technical crew members.

Key Findings and Requirements:

- **User-friendly interfaces:** Experts emphasized the importance of simplified, intuitive interfaces to enable non-technical crew members (e.g., set designers, directors) to interact with virtual environments without needing advanced technical skills (P1, P2).
- **Motion-capable outputs:** NeRF and Gaussian Splatting were highlighted as promising, but their inability to handle dynamic elements (e.g., moving objects in car chases) limits their broader application in virtual production (P1, P5).
- **Dual-mode operation:** Flexibility to switch between VR and tablet modes was seen as critical to suit different production contexts. While VR is valuable for immersive set walk-throughs, tablet-based operation remains necessary for broader adoption (P1, P3).
- **Set walk-throughs and location scouting:** AI-generated environments were seen as valuable for pre-production tasks like set walk-throughs and location scouting, currently rarely used due to the need for specialized software and customization, limiting them to more technical users (P1, P2, P3).
- **Marking and annotation tools:** Participants suggested adding features to mark specific locations within environments (e.g., height measurements, lighting placements) to improve communication between departments (P1, P2).
- **Customization options:** Experts expressed the wish for customization like adjusting art direction on the fly and positioning objects or characters to effectively stage a scene (P2).
- **Comprehensive decision matrix:** A guide to help filmmakers choose the most appropriate AI tools based on the production task (e.g., quick ideation vs. detailed previsualization) would streamline workflows and improve decision-making (P3, P5).

3.2 Impact on Design

These insights informed the development of the prototype's current and future design, emphasizing ease of use, motion support, and flexibility. By incorporating intuitive interfaces and preparing for flexible interaction modes in the future, the prototype was designed to bridge the gap between technical expertise and creative needs. The feedback provided clear direction for future development, ensuring that the tools are practical, accessible, and aligned with industry workflows.

Table 1: Overview of key filmmaking tools for media review, scouting, and previsualization relevant to AI-generated environments.

Category	Tool Name	Key Use	Key Features
Media Review	<i>CineSync</i>	Scene reviews	- Frame-accurate annotations - Synchronized playback - Remote collaboration
	<i>SyncSketch</i>	Real-time feedback	- Sketch tools - 3D model review - Asynchronous collaboration
Scouting/Previs	<i>Unreal Engine Virtual Scouting</i>	Previs and VR support	- Real-time rendering - VR support - Extensive assets library
	<i>Unity Reflect</i>	AR/VR collaboration	- Real-time rendering - AR/VR walkthroughs - Collaboration tools
	<i>CineTracer</i>	Real-time cinematography	- Simulated lighting - Set design - Camera control
Real-Time VP/AR Tracking	<i>CamTrackAR</i>	Real-time camera tracking	- AR-based tracking - Seamless scene integration - Mobile device compatibility
	<i>SkyGlass</i>	AR virtual production	- Real-time visualization - AI-assisted tracking - Integration with VP workflows
	<i>Lightcraft Jetset</i>	Virtual production compositing	- Real-time compositing - Hardware integration - Precision tracking
3D Scanning	<i>Matterport</i>	Virtual scouting	- 3D space capture - Virtual tours - High-resolution scanning

4 EnVisualAlzer Prototype

4.1 Design Approach

The prototype was developed to provide filmmakers with an accessible platform for exploring and evaluating AI-generated environments. The design process focused on creating an intuitive interface for previsualization and scene creation led by mapped-out user flow diagrams. Initial low-fidelity wireframes were sketched in Procreate¹⁸ and refined through Figma¹⁹ to ensure ease of navigation and a streamlined experience for users from diverse filmmaking backgrounds.

4.2 Technical Implementation

We implemented the prototype using *Unreal Engine 5* for its real-time rendering capabilities and multi-platform support, integrating the *Volinga.ai* plugin [53] to render Gaussian Splatting environments efficiently for high-fidelity 3D scenes. We employed *Firebase* [26] for cloud-based project management, allowing seamless user and data handling across platforms. A key feature is the integration of the *Stable Diffusion API* [11], enabling users to generate and modify images directly within the application and supporting on-the-fly iteration during previsualization. While not all expert recommendations, such as motion-capable outputs for NeRFs and

Gaussian Splatting, were immediately implementable, the system's flexibility and scalability provide a strong foundation for future enhancements.

4.3 System Walkthrough and Features

The *EnVisualAlzer* prototype offers a simple user interface with several key views, which can be seen in Figure 1 and 2:

Home/Project Dashboard: Users can manage multiple projects, view recent activities, and access shared assets.

Environment Exploration View: Users interact with AI-generated environments, adjusting camera angles, and adding annotations or markers.

Previsualization Mode: Offers customizable camera settings, allowing filmmakers to adjust and save different scene configurations for later review.

Key features of the prototype are directly based on insights from expert interviews and the study of related tools, addressing specific industry needs (see Table 2 for feature origins).

4.4 Explored Environment Types

Throughout the design process, we experimented with various AI environments and selected the following three for their optimal balance of ease of integration and creative flexibility (see Figure 3):

¹⁸Procreate. Digital art tool. Available at <https://procreate.art/>

¹⁹Figma. UI/UX design tool. Available at <https://www.figma.com/>

²⁰Mixamo. Animation and Rigging. Available at <https://www.mixamo.com>

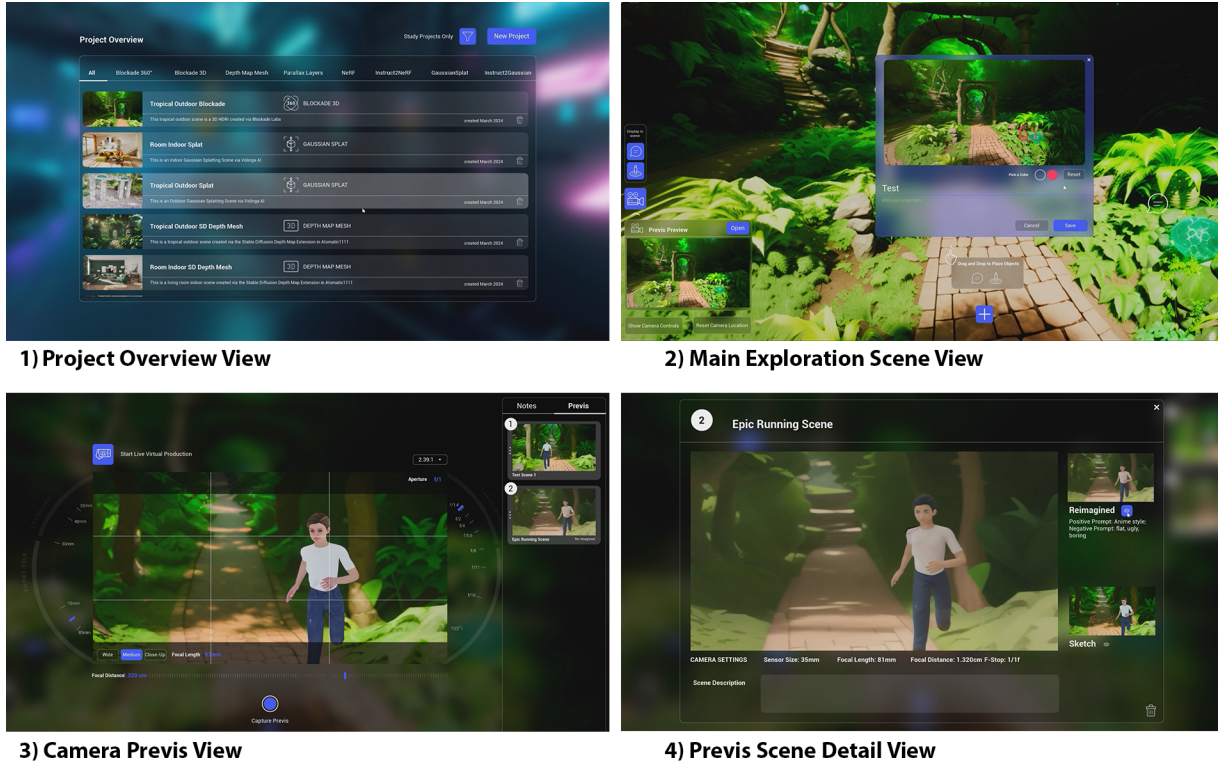


Figure 2: Overview of the main views of the *EnVisualAIzer* prototype: (1) Sample project selection, (2) the explorable scene with note and character placement, (3) the camera previs mode, and (4) a detailed view of a saved scene showcasing an Image2Image adjustment.

Table 2: Key features of the *EnvisualAIzer* prototype and their origins from expert feedback and related tools.

Key Feature	Source	Description
Real-time feedback and annotation	Expert interviews (P1, P2) Related tools (CineSync, SyncSketch)	Provides immediate adjustments and annotations within environments for rapid iteration
Camera control for previsualization	Expert interviews (P1, P2, P3) Related tools (SyncSketch)	Enables dynamic camera settings and scene configuration storage
Dual-mode operation compatibility	Expert interviews (P1, P3) Related tools (Matterport, SyncSketch)	Provides multi-platform support for immersive (VR) and non-immersive (tablet) interaction
Image2Image Customization	Expert interviews (P2)	Supports image generation and customization on-the-fly for flexible art direction
Character Placement	Expert interviews (P2)	Allows users to place and manipulate characters (3D models and poses via <i>Mixamo</i> ²⁰) within the environment to stage scenes effectively

Inpainted meshes generated from depth maps: These environments were integrated via Stable Diffusion’s Automatic1111 WebUI [1] Depth extension [50]. They are 3D models created from 2D images by analyzing and interpreting depth information. These meshes use a depth map—a grayscale representation of how far each part of the image is from the viewer—to construct a 3D surface.

The process essentially “stretches” the flat image into a 3D space, creating a scene with visible depth and perspective. However, the resulting mesh often appears distorted or elongated because the depth map can only approximate 3D structure from a single view-point. These meshes are not fully realistic but are functional for exploring spatial relationships and allow for basic 3D interaction and scene exploration.



Figure 3: Overview of the six demo environments: three AI environment types (1) Depth Mesh, (2) Blockade 360° Panoramic Images, and (3) Vologga Gaussian Splat, in an indoor and outdoor setting each.

360° HDRI scenes from Blockade Labs: These environments were generated as 360° spherical panoramas, which, when viewed in their intended form, create a fully immersive scene. These panoramas are mapped onto a deformed sphere, allowing users to look around the environment as if they were standing inside it. When converted into 3D meshes, the environments maintain their panoramic nature but take on a warped, dome-like appearance. These meshes are not perfect representations of physical spaces but rather approximations that give a sense of depth and dimension. Surfaces can sometimes appear stretched or distorted, especially at the edges, due to the nature of mapping a flat equirectangular image onto a 3D surface. The Blockade Labs online platform allows for the rapid creation of such environments from text prompts with the optional help of sketches and outlines as guides.

3D Gaussian Splatting environments: For scene reconstruction, we chose Gaussian Splatting due to its superior rendering speed and real-time compatibility compared to NeRF, allowing users to dynamically explore environments with minimal latency. Its universal .ply format also simplifies integration into virtual production workflows and game engines. For the prototype, the Vologga Unreal Engine plugin was used to integrate pre-made splats from *Vologga.ai* and *Polycam*²¹, ensuring high-quality and reproducible environments.

²¹Polycam: 3D Scanning Software with 3DGS Support. Available at <https://polycam.com>

5 Exploratory Expert Evaluation

This exploratory study assessed the novelty of integrating AI-generated environments in filmmaking workflows, focusing on previsualization, creativity, and efficiency. Building on the initial, more technically focused expert interviews, the second round expanded to include diverse departments to gain broader insights. Using the prototype as a testbed, participants assessed different environment types for their characteristics and applicability across production stages. Predefined evaluation criteria ensured quantifiable results.

Study Design: We based the study on the hypothesis that AI-generated environments could streamline previsualization, support rapid prototyping, and enhance production efficiency. Rather than focusing on the usability of the prototype, participants were encouraged to engage with the environments using features like camera control, annotation tools, and previsualization modes. The focused sample of 15 filmmakers provided in-depth, qualitative insights, making this an important exploratory step in a field with limited prior research. The diverse feedback gathered offers a valuable foundation for understanding how AI-generated environments can transform production workflows and will inform future, more extensive studies.

Participants and Procedure: To ensure a wide range of perspectives, the study was conducted as a controlled lab experiment involving 15 participants with diverse filmmaking backgrounds. We were able to engage subjects from a film school context, including film students, seasoned professionals, and three amateur filmmakers, each with varying levels of experience in the industry. Participants' roles spanned pre-production, production, and post-production, providing insights from departments such as cinematography, editing, screenwriting, VFX, and directing. The age range was 21 to 48, ensuring representation from both emerging talents and more established professionals. This diversity, despite the small sample size, offered a comprehensive view of how AI-generated environments could impact different stages of the filmmaking process.

Each session lasted between 90 and 120 minutes and followed a structured process:

- (1) **Onboarding:** Participants were introduced to the study's goals, provided demographic information, and completed a pre-assessment questionnaire regarding their professional background and familiarity with AI tools in media production.
- (2) **Environment Exploration:** Participants explored six AI-generated environments, sharing their thoughts during the interaction. After each exploration, they completed a questionnaire to evaluate the environment's characteristics and its potential usefulness in production workflows.
- (3) **Conclusive Interview:** Informal interviews gathered qualitative insights about the environments and their creative potential and suggestions for improvement.

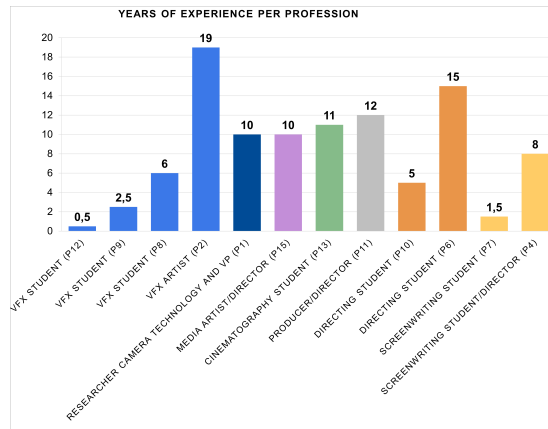


Figure 4: Years of experience per profession for each of the twelve professional participants.

Test Conditions: The study evaluated three types of AI-generated environments: Depth Map Mesh, Blockade Labs 360° HDRI to 3D Mesh, and Gaussian Splatting. Each type was presented in two distinct settings: an *indoor living room* and an *outdoor tropical landscape*. These six variations, presented in a systematically randomized order, allowed participants to experience different levels of realism and interactivity, providing a holistic view of how each method could be applied to VP.

Evaluation Criteria: The evaluation criteria were carefully designed to assess both the technical and creative potential of AI-generated environments in filmmaking. Grounded in expert feedback and existing research on quality assessment for AI-generated content [40, 54, 58, 61], the criteria focused on aspects such as *realism*, *visual quality*, *level of detail*, and *creative impact*, rated on a five-point Likert scale. These dimensions were chosen to capture both the fidelity of the environments and their practical utility in production workflows. Our custom-designed questionnaire drew on established HCI evaluation tools, such as the *Presence Questionnaire (PQ)* [56] for assessing immersion, and *AttrakDiff* [20] for measuring user satisfaction and engagement, but was adapted specifically to gauge the environments' ability to enhance previsualization and creativity in virtual production settings.

Data Collection Methods: A mixed-methods approach was adopted to gather both quantitative and qualitative data. Adding to the quantitative online questionnaire²² ratings, for qualitative data, participants provided open-ended feedback during an informal interview, allowing them to share their impressions, preferences, and ideas for improving the environments. All interviews were transcribed and analyzed using thematic analysis following the guidelines of Braun & Clarke[4]. We used MaxQDA²³ to code and categorize the data, allowing for the identification of recurring themes, patterns, and contrasts across participants. This approach enabled us to systematically analyze qualitative insights in relation

to participants' roles, tool usage, and perceptions of creative potential. Emerging codes were iteratively refined into overarching themes. The think-aloud method was also employed during the exploration phase, capturing real-time cognitive reactions and insights as participants interacted with the environments. These qualitative insights provided rich, detailed feedback, offering a nuanced understanding of the environments' strengths and limitations.

6 Results

6.1 Quantitative Results

We analyzed users' Likert scale ratings through descriptive statistics like mean values (M) and standard deviations (SD), offering valuable preliminary insights that serve as a foundation for future research.

Gaussian Splatting emerged as the highest-rated environment, particularly for indoor settings. It scored particularly well for its characteristics parallax effect ($M = 3.80$), usable area ($M = 3.47$), and visual aesthetics ($M = 3.20$) compared to the others (see Figure 5 and Appendix C). In terms of creative impact, Gaussian Splatting was rated highly for enabling participants to achieve their vision ($M = 3.40$) and fostering creativity ($M = 3.53$). This environment was particularly suited for previsualization, storyboarding, and concept development, with scores often exceeding 4.0 in these areas.

Blockade 3D had a mixed performance. It was particularly effective in outdoor settings, where it scored well for sparking creativity (outdoor $M = 3.07$) and moodboards/concept development (outdoor $M = 3.60$). However, it lagged behind Gaussian Splatting in visual quality and realism, and its navigability was often cited as a drawback, limiting its broader application in final production phases.

Depth Mesh consistently received the lowest ratings. It scored poorly for visual quality (outdoor $M = 2.67$) and realism. However, participants found it somewhat useful for moodboards and concept development (indoor $M = 3.07$), making it suitable for early-stage production tasks but not for high-fidelity previsualization.

Standard Deviation Insights: The analysis of standard deviations revealed significant variability in participants' ratings, particularly for Depth Mesh and Blockade 3D. Values around 1 were common, indicating a diverse range of opinions. For example, Depth Mesh in outdoor settings had an SD for the level of detail ($SD = 1.33$) and usable area ($SD = 1.70$), suggesting mixed experiences with depth perception and spatial usability. Blockade 3D also showed variability, with outdoor settings for moodboard suitability ($SD = 1.18$). Although Gaussian Splatting was the most highly rated overall, it exhibited variability, particularly in outdoor settings for visual quality ($SD = 1.08$), suggesting it holds significant potential but may not deliver consistent results across all settings.

6.2 Qualitative Results

As qualitative feedback participants provided detailed insights into each environment's strengths and limitations, offering practical suggestions for improvement.

²²LimeSurvey. Online Survey Tool. Available at <https://www.limesurvey.org>

²³MaxQDA. Qualitative Data Analysis Tool. Available at <https://www.maxqda.com/>

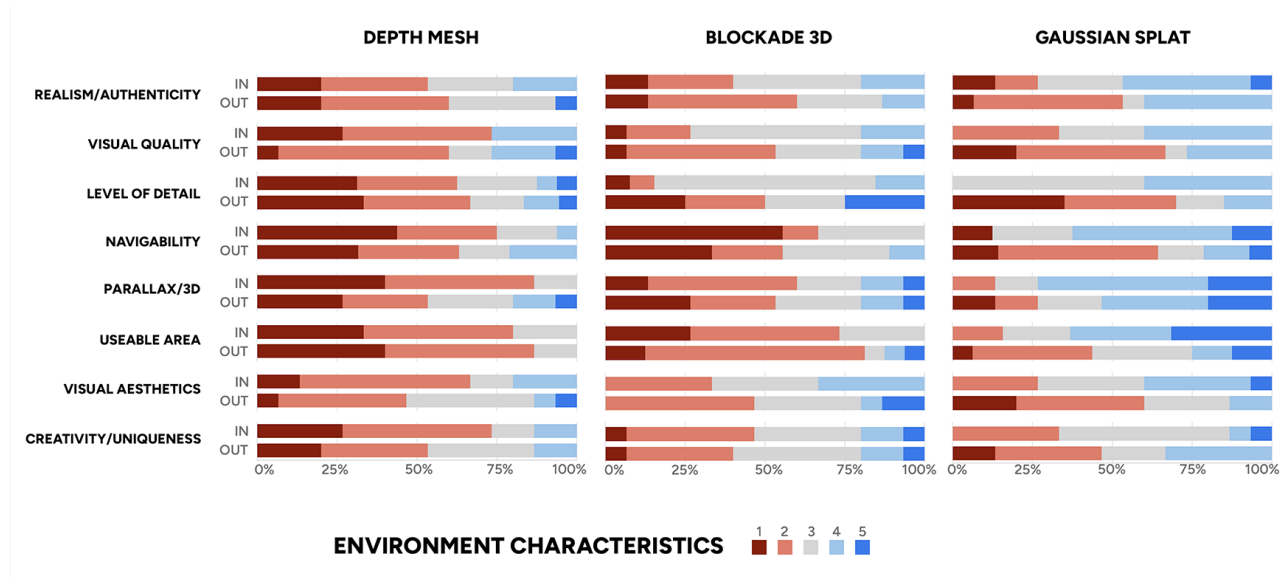


Figure 5: Stacked bar charts illustrating user ratings regarding environment characteristics per environment type on a Likert scale; red hues indicate low ratings, light grey neutral ones, blue positive ones.

Gaussian Splatting was widely praised for its immersive qualities, which allowed for greater flexibility in previsualization and scene exploration (P1, P5). Participants noted that it offered a strong sense of depth and realism, particularly in indoor settings (P11). However, some participants expressed a desire for higher resolution and more accurate depth of field, especially for outdoor environments (P2, P6). Several users suggested that Gaussian Splatting could be further enhanced with motion integration and dynamic lighting, which would make it more suitable for the final production phases (P3, P12). One participant highlighted its potential for creating highly stylized scenes, such as dream sequences or surreal environments, due to its unique visual style (P14).

Blockade 3D was appreciated for its ability to quickly generate environments and support early-stage production tasks like mood boards and concept development (P5, P8). Participants noted that it was particularly useful for visualizing large outdoor scenes, where its 360° view allowed for a comprehensive exploration of the environment (P7, P10). However, limitations in navigability and depth perception were common complaints, with several participants mentioning difficulties in moving around the environment and interacting with objects (P8, P9, P12). Some participants suggested that Blockade 3D would be better suited for low-fidelity tasks like storyboarding or rough previsualization, rather than final production (P7, P14).

Depth Mesh, while rated lower overall, was still recognized for its utility in specific contexts. Participants found it useful for quickly setting up basic scenes and experimenting with different camera angles (P1, P5, P7). However, its visual quality and realism were frequently criticized, with many noting significant distortion and a lack of depth in both indoor and outdoor settings (P1, P8, P12).

Despite these limitations, participants saw the potential for Depth Mesh in early-stage production phases, particularly for concept development and rough visualization (P3, P6, P10).

6.3 Profession-Specific Insights and Workflows

Participants' workflows and goals varied based on their professional roles, highlighting the distinct ways AI-generated environments were utilized. Directing students (P6, P10) primarily used Blockade 3D for concept development and communication, leveraging its rapid environment generation to create mood boards and explore initial ideas. One directing student noted, "*The quick environment creation really helps to get ideas across to my team without spending too much time on manual sketches. (P10)*" The cinematography student (P13) found Gaussian Splatting particularly useful for testing camera angles and shot composition, citing its strong depth and realism but emphasizing the need for improved lighting control to better simulate real-world conditions. The student remarked, "*It provides a great sense of space, but I'd love more control over lighting adjustments to better plan shots.*" Screenwriting students and directors (P4, P7) favored Depth Mesh for early-stage scene planning, appreciating its ability to quickly establish spatial relationships despite its visual limitations. They suggested refining texture quality and adding interactive elements to enhance its utility for storytelling and visualization. VFX students and artists (P2, P8, P9, P12) identified Gaussian Splatting as particularly useful for stylized backdrops, describing it as "*a great tool for creating stylized backdrops that blend seamlessly with live-action elements. (P9)*" However, they highlighted the need for higher resolution and object tracking features to align with professional pipelines. Producers and directors (P11, P15) valued the environments for planning and budgeting, stressing intuitive navigation and robust collaboration features to support team discussions. The researcher in camera technology and

VP (P1) emphasized their potential for experimental applications and technical visualization, particularly in studying different camera setups. Across all roles, participants consistently emphasized the need for improved interactivity and customization to better align the tools with their professional workflows.

Across all environments, participants highlighted the need for greater usability and flexibility, suggesting several improvements discussed below. Despite low quantitative ratings, in conversation, participants expressed optimism about incorporating these tools into their workflows with further development.

7 Discussion

This discussion reflects on the study’s findings, exploring the strengths and limitations of the three AI-generated environments—Depth Mesh, Blockade 3D, and Gaussian Splatting—across different settings.

Effectiveness and Suitability of AI-Generated Environments:

The findings revealed that Gaussian Splatting consistently outperformed the other techniques due to its ability to create immersive, detailed environments. Blockade 3D excelled in outdoor environments and early-stage tasks such as concept development and moodboards but lacked the depth required for high-end production. Depth Mesh, though limited in realism, proved useful for quick, low-fidelity tasks like initial scene setup. These results affirm the initial expert feedback that AI environments could enhance previsualization and creative workflows, but more development is needed for widespread industry adoption.

Ambiguous Rating System and Limitations of Evaluation Metrics:

One issue identified was the ambiguity in rating usefulness across production stages and application areas. Participants struggled to separate these categories, as an environment might be suited for previsualization but not final production, likely contributing to higher standard deviations and user uncertainty. Additionally, the discrepancy between indoor and outdoor ratings for Gaussian Splatting may reflect a bias due to the specific environments chosen from different providers. Selection bias may have influenced participant ratings across all environments. The probable interdependence between characteristics (e.g., visual quality, realism) and creative impact was also evident, with low ratings in one influencing the other. However, artifacts in Gaussian Splatting sparked creative ideas despite lower technical ratings. While this study focuses on the technical and creative potential of AI-generated environments, it does not aim to address ethical considerations such as authenticity, cultural representation, or broader societal implications of these technologies. These topics are undoubtedly important but fall outside the scope of this research and require dedicated inquiry to explore their complexities in depth.

Prototype Limitations and Improvements: Participants cited usability issues in navigation and object placement, indicating the need for more intuitive controls. They suggested "snap to ground" features and multi-view navigation to make the interface more intuitive. The limited visual quality of the environments, particularly in

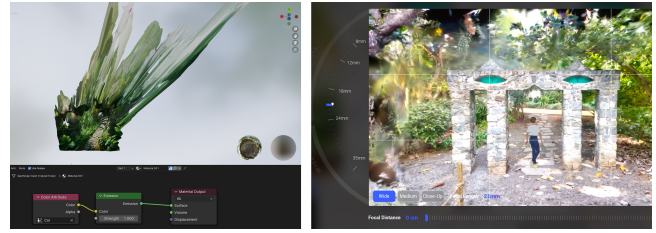


Figure 6: Left: View of the Depth Mesh outdoor environment in Blender, revealing its full distortion; Right: Screenshot of user interaction in the outdoor Splat, revealing artifacts around the frame edges.

Depth Mesh and Blockade 3D, was another concern that negatively impacted user experience independently from the UI. Improving visual fidelity and incorporating real-time collaboration would increase applicability for more professional filmmaking contexts.

Creative Potential and Unexpected Applications: Creative potential was recognized across various filmmaking tasks, with directors wanting to use the environments to communicate ideas more easily than traditional sketches, producers to scout locations, and screenwriters to imagine worlds and spark new ideas. Participants found artistic value in the imperfections of the environments (see Figure 6). For instance, the distortion in Depth Mesh inspired ideas for transitions or "dream-like" scenes, while the "painterly" quality of 3DGS encouraged experimentation with stylized visuals. These findings suggest that, while the environments may not yet be ideal for high-fidelity production, they hold promise for experimental projects such as music videos or animations.

Co-Creation with AI: Our findings align with the growing trend of co-creating with AI, where users collaborate with AI tools to enhance creative outcomes. Participants expressed a desire for more control over environments, such as editing lighting and manipulating scene elements. This mirrors broader developments in AI-assisted creativity, with tools like *StoryPrompt* [14] and *XCreation* [60] demonstrating the value of user-AI collaboration in storytelling and design. In VP, interactive tools could foster creativity by enabling filmmakers to work with AI in real-time, rather than relying solely on post-generation editing.

Addressing Specific User Feedback: User feedback has identified several areas for improvement to enhance the usability and functionality of AI-generated environments, which align with current research trends and emerging technologies. Key areas for future work include the following:

- **Environment Editing and Relighting:** Improving the ability to edit and relight scenes, especially in 3DGS, would enable real-time adjustments to lighting and scene elements. Research such as Gao et al.’s [17] work on *Relightable 3D Gaussians* and the development of *Instruct-GS2GS* [51] offers potential for enabling dynamic lighting and stylization in AI-generated environments.

- **Dynamic Scenes:** Incorporating dynamic elements, like moving objects and lighting changes, would make these environments more applicable for later stages of production. Current advances in *dynamic 3D Gaussians* [29] and *4DGS* [57] are paving the way for motion-capable AI environments, which could significantly improve realism and flexibility.
- **XR/AR Integration:** XR/AR offers vast potential for immersive previsualization and virtual production. Preliminary exploration of this concept in tools like Unreal Engine Virtual Scouting [16] suggests promising applications for AI-generated environments in both VR and AR, particularly for tasks like set walk-throughs and interaction with virtual models.

Recent Industry Developments: The rapid adoption of AI in virtual production has led to the emergence of new tools and features that align with our research findings. Notably, after our study, several products have been introduced or updated with capabilities similar to those we explored. For instance, *Previs Pro*²⁴ has integrated AI to assist in creating props and style grading—similar to our *img2img* modification mode—to enhance the previsualization process. Similarly, *Cuebric*²⁵, as a more holistic tool, offers advanced AI functionalities, including generative mesh creation with camera simulation, image generation, and inpainting, facilitating the generation and editing of virtual environments. In addition, *Skyglass* has announced upcoming AI features such as text-to-video B-roll generation, real-time foreground effects, and 3D scene layout customization, further highlighting the growing trend of integrating AI to enhance production efficiency and creative flexibility. These developments affirm the relevance of our work and suggest a growing industry trend toward incorporating AI-driven tools in virtual production.

Ethics and Authorship: Although ethical and authorship concerns were not prominently raised by participants in this study, their relevance is increasing in the context of AI-driven creative workflows. Emerging questions include the intellectual ownership of AI-generated environments, transparency in generative processes, concerns about authenticity and cultural representation in AI-generated visuals, and the cultural implications of automated content production [2, 3, 6, 12, 31, 41]. In virtual production, where designers and directors engage generative tools to co-create visual elements, authorship becomes both ethically and legally significant. VFX professionals express concern over the erosion of creative credit when AI tools are trained on their work without attribution [36]. Bozkurt highlights the “organic vs. synthetic” paradox in authorship, calling for transparency and acknowledgment practices that respect human input [3]. Recent work suggests moving beyond binary definitions of authorship toward models of iterative co-creation, where human agency is exercised through prompting, curating, and refining generative output [31, 41]. Addressing these ethical dimensions is its own research area and will be essential as generative design tools become further embedded in media production pipelines.

²⁴Previs Pro. AI-powered previsualization tool. Available at <https://www.previspro.com/>

²⁵Cuebric. AI-enhanced virtual production tool. Available at <https://cuebric.com/>

Our findings offer promising insights into the potential of AI-generated environments in filmmaking, revealing their strengths and limitations across production stages. However, as an exploratory study based on a small and diverse sample ($n=15$), the results are not broadly generalizable. This work should be viewed as a foundational step—one that identifies early patterns, generates hypotheses, and informs future research. Continued investigation is needed to validate these findings, refine evaluation methods, and assess applicability across roles and workflows. As similar tools see rapid adoption in industry, future studies will scale up to larger, role-specific cohorts and aim to support the development of optimized, AI-enhanced production pipelines.

8 Future Work

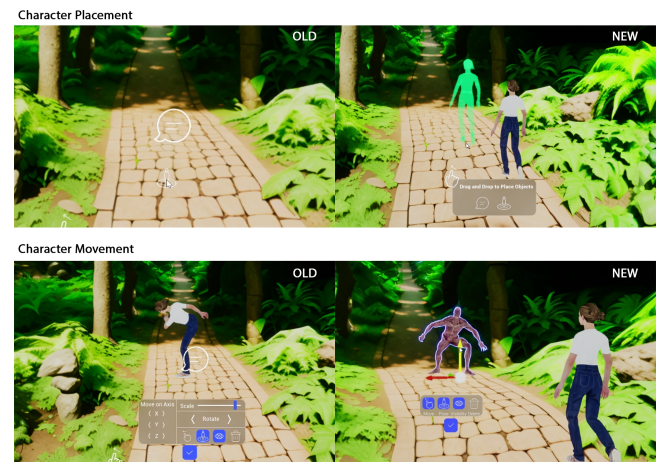


Figure 7: Comparison of the old implementations of character placement and movement with the new ones providing advanced preview capabilities in 3D space with color indicating placement validity (green=valid, red=invalid), a “snap-to-ground” feature, as well as easier movement via gizmos instead of individual buttons.

Prototype Refinement: Future work will focus on further refining the *EnVisualAizer* prototype to enhance flexibility and accessibility, addressing key areas highlighted by participants. Recent improvements include the implementation of “snap to ground” and drag-and-drop object placement, making navigation more intuitive (see Figure 7). For Gaussian Splatting, easier navigation is also enforced by switching to the Luma UE5 plugin [30] (see Figure 8). In progress is the integration of animated previsualization capabilities through Luma’s *DreamMachine API*²⁶, enabling seamless image-to-video generation for dynamic scene planning. Figure 9 shows a new details display for each scene with the option to create an animatic, as well as the UI for configuring the animatic’s video generation. Ongoing development will prioritize essential features such as multi-view functionality, real-time collaboration, and XR

²⁶DreamMachine. AI-powered image-to-video generation tool. Available at <https://lumalabs.ai/dream-machine/api>

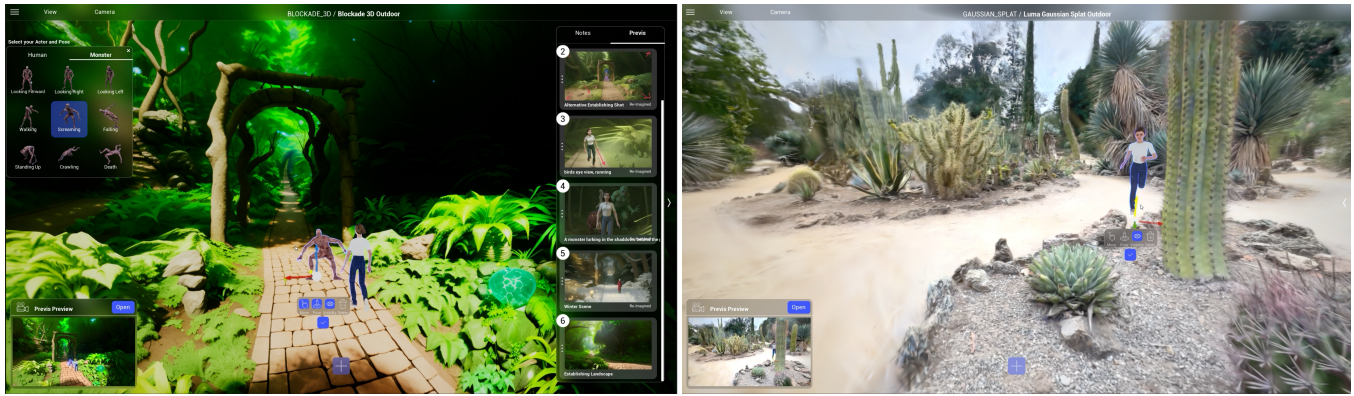


Figure 8: Two environment settings in exploration mode, showcasing an updated UI. Left: Blockade 3D Outdoor Environment with UI elements for character pose selection, previs preview, and scene management. Right: Luma AI Gaussian Splat Outdoor Scene with an interactive UI for object placement and preview.

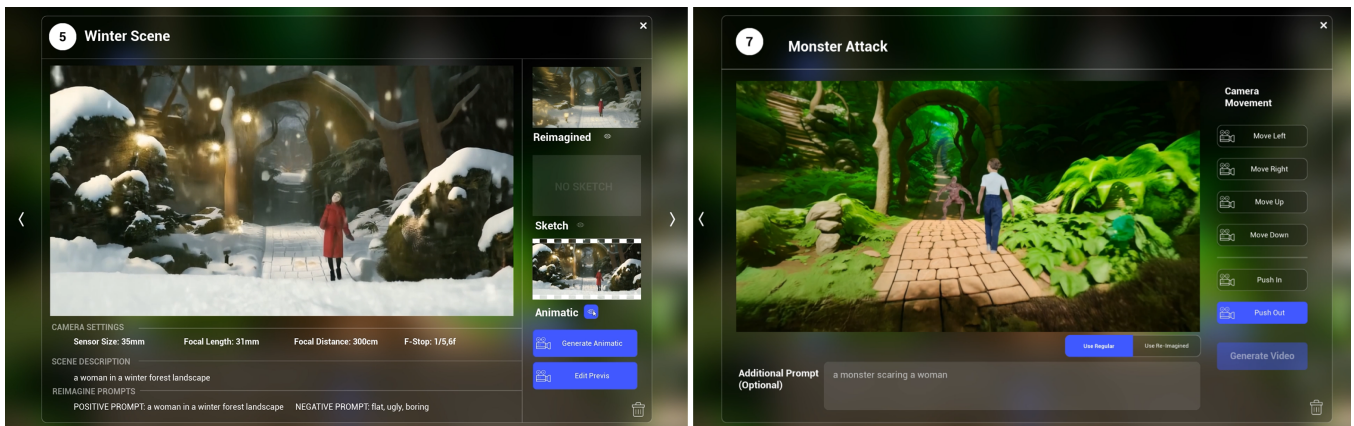


Figure 9: Updated previs scene detail windows. Left: The "Winter Scene" overview displays information such as whether the scene was reimagined using Img2Img generation, the presence of sketches or animatics, camera parameters, a scene description, and reimage prompt details. It also provides options to edit the previs or generate an animatic. Right: The "Monster Attack" animatic generation window features options to select between a regular or reimagined scene, input an additional prompt, and choose from preset camera movement options, such as move left, push in, or push out, before generating a video.

integration to support immersive previsualization workflows. Additionally, expanding generative capabilities to include assets such as props and characters, along with pose manipulation tools, will further increase the tool's versatility across various filmmaking stages. These advancements aim to position *EnVisualAizer* as a comprehensive and adaptable solution for professional virtual production environments.

Towards Tailored Interaction for Specific User Groups: While the initial prototype demonstrated the potential of AI-generated environments, interactions and feedback were limited to general use cases rather than tailored to specific user groups, such as cinematographers or production designers. These professionals bring domain-specific insights that could significantly enhance the relevance and usability of the tool. Engaging production designers during the initial exploration proved challenging due to limited

availability. Future iterations of the prototype aim to address these gaps by incorporating user-centered design approaches and actively involving these groups in the design and evaluation processes. A key focus will be the integration of real foreground props with virtual elements, a crucial requirement for production designers to achieve seamless blending of physical and digital components. UI, layouts, and interaction tools could be tailored to the goals of each user group, similar to the concept of workspaces in Photoshop or Blender. As an initial step in this direction, a top navigation bar with customizable, toggleable screen overlays has already been implemented.

Addressing Industry Adoption Challenges: To move *EnVisualAizer* from prototype to practical tool, future work must address key barriers to industry integration. Existing VFX pipelines rely on established proprietary tools, making new systems difficult to

adopt, even in innovation-driven environments [36]. For high-end workflows, support for final-pixel output is essential, including precise color space handling, high rendering fidelity, and modular environments with relighting and editable elements. Compatibility with industry-standard software such as Maya, Nuke, and Houdini is a prerequisite. While the current system accelerates ideation and automates routine tasks, production-ready results still require human refinement [36]. Ethical concerns such as authorship and data provenance need to be handled. Additional challenges include hardware requirements, cloud access restrictions, and limited onboarding pathways for new users. To overcome these limitations, future development will prioritize plugin-based interoperability, standardized format support, and enhanced editing features within the tool. Role-specific onboarding and customizable interfaces will improve accessibility across departments. Co-design sessions and pilot deployments with studios will ensure that EnVisualAlzer evolves into a production-ready tool aligned with real-world workflows.

Exploration of Emerging Approaches: As immediate usability challenges are addressed, exploring emerging AI-driven approaches offers a path to extend EnVisualAlzer toward dynamic, real-time, and interactive virtual production. These advances inform its long-term roadmap, especially as the prototype moves beyond static scene exploration. Recent advancements in video generation are transforming AI-created environments into dynamic and interactive "world models," a term originally introduced to describe systems that simulate an agent's understanding of its environment for decision-making and prediction [19]. These models go beyond static renders, creating immersive simulations that incorporate physical and temporal consistency. Video models like OpenAI's Sora²⁷, RunwayML's Gen-3²⁸ or Genmo's Mochi 1²⁹ exemplify this by using scalable diffusion-based methods to generate high-quality, temporally coherent videos across various formats, establishing the foundation for scalable simulations [5, 8]. World Labs announces advancing this concept by turning single 2D images into fully interactive 3D environments, offering stable, editable scenes aligned with basic physical principles [55]. Real-time systems like *Oasis* [13] and *GameNGen* [52] demonstrate the potential of world models in interactive applications, producing environments that respond dynamically to user input, making them ideal for gaming and simulations [10, 52]. Although these technologies are groundbreaking, challenges such as maintaining long-term consistency and aligning output with user intentions remain. Techniques like Diffusion Forcing and guided AI are helping to address these issues, improving stability and responsiveness [8]. These developments open new possibilities for filmmaking, enabling creators to design real-time, camera-reactive environments that redefine storytelling and creative control within a whole new interaction paradigm.

Advanced Follow-Up Studies: To strengthen the reliability and generalizability of our findings, we plan to expand our participant

pool in future studies. This will include targeted, role-specific evaluations with production designers, cinematographers, and other domain experts, as well as collaborations with larger studios. These efforts will allow us to examine the impact of AI-generated environments across a broader range of production contexts and workflows. Future studies will focus on evaluating the tool's usability across specific filmmaking roles through structured usability questionnaires like the User Experience Questionnaire (UEQ) [27] or Attrakdiff [20]. Comparative assessments against industry-standard and emerging AI tools will provide insights into production speed, creative efficiency, and workflow integration. Testing interdisciplinary collaboration methods—between e.g. production designers, directors, and cinematographers—will help refine communication and coordination strategies within AI-driven workflows. Additionally, research will explore optimal AI prompting methods for content generation and the effectiveness of different input modalities, such as tablets, desktops, and immersive AR/VR systems. Expanding the participant pool with larger sample sizes and diverse production contexts will further validate the tool's applicability and scalability.

9 Conclusion

This exploratory study investigated the creative potential of AI-generated environments in virtual film productions, providing insight into how these technologies can enhance creative workflows in concept development and proposes enhancement ideas to provide value across various production phases. By evaluating Depth Mesh, Blockade 3D, and Gaussian Splatting, we demonstrated their respective strengths: Gaussian Splatting excelled in detailed pre-visualization, Blockade 3D was valuable for early-stage tasks like moodboards, and Depth Mesh, though limited in realism, provided utility for quick scene setups. While the findings were largely unsurprising and aligned with anticipated capabilities, they manifest these insights in a measurable and empirical manner, providing a clear validation of the practical applications of these tools. Our findings highlight the early-stage development of these tools and reveal opportunities for improvement in dynamic scenes, real-time collaboration, and visual fidelity. This study contributes to ongoing research on AI-supported filmmaking, offering a foundation for future work aimed at refining AI tools and validating their effectiveness in further studies, ultimately shaping the future of AI-driven creativity in filmmaking.

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A Preliminary Expert Interview Questions

- How do you currently use virtual environments in different stages of film production (pre-production, production, and post-production)?
- What are the strengths and limitations of current virtual production tools (e.g., Blockade Labs, NeRF, 3D Gaussian Splatting) in your experience?
- How could AI-generated environments enhance creative workflows, and what specific improvements would you like to see in such tools?
- What challenges do non-technical users face when interacting with virtual environments, and how could these be addressed in terms of usability?
- What features would be most beneficial for collaborative work on virtual environments across different film departments?

B Qualitative Assessment Criteria for AI Generated Environments

Environment Characteristics: *In the following, you are asked to rate particular aspects of the environment from 1 (low) to 5 (high).*

- **EC1:** Realism/Authenticity
- **EC2:** Visual Quality
- **EC3:** Level of Detail
- **EC4:** Navigability
- **EC5:** Parallax Effect/3-Dimensionality
- **EC6:** Usable Area
- **EC7:** Visual Aesthetics
- **EC8:** Creativity/Uniqueness

Creative Impact: *In the following, we would like to explore how much the AI environment supported your creative workflow. Please rate how much you agree with the statements below from 1 (don't agree at all) to 5 (fully agree).*

- **CI1:** The environment was engaging.
- **CI2:** The environment allowed me to explore many different ideas, options, designs or outcomes.
- **CI3:** The environment allowed me to achieve the vision in my head.
- **CI4:** The environment supported my creativity and sparked new ideas.
- **CI5:** I am satisfied with the results I got from the environment.

Production Phase: *Please rate from 1 (low) to 5 (high) how useful you consider the environment for the following production steps/phases.*

- **PP1:** Moodboard/Ideation/Concept Development
- **PP2:** Storyboards/Animatics (Low-Fi)
- **PP3:** Pre-visualization (Hi-Fi)
- **PP4:** Tech-Vis/Set-Tests
- **PP5:** Final Production (LED/Green-Screen)

Area of Application: *Please rate from 1 (low) to 5 (high) how useful you consider the environment for the following types of productions and areas of application.*

- **AA1:** Virtual Film Productions (Mix of real and digital content)
- **AA2:** Fully Digital Productions (e.g., Animation)

- **AA3:** Television Sets
- **AA4:** Web-Formats (Youtube, Social Media...)
- **AA5:** Live Performances/Events
- **AA6:** High-End Productions
- **AA7:** Amateur/Independent Productions

C Quantitative Data

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Table 3: Comparison of average ratings (Mean) and standard deviations (SD) for various environment characteristics across the different types and settings given on a Likert scale from 1 (low) to 5 (high).

Environment Type	Setting	Realism/ Authenticity		Visual Quality		Level of Detail		Naviga- bility		Parallax Effect/3D		Useable Area		Visual Aesthetics		Creativity/ Uniqueness	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Depth Mesh	indoor	2.47	1.06	2.27	1.16	2.27	1.22	1.87	0.99	1.73	0.70	1.87	0.74	2.40	0.99	2.13	0.99
	outdoor	2.33	1.05	2.67	1.11	2.27	1.33	2.33	1.29	2.47	1.25	1.73	0.70	2.67	0.98	2.40	0.99
Blockade 3D	indoor	2.67	0.98	2.87	0.83	2.80	0.77	1.87	0.74	1.80	0.87	2.00	0.76	3.00	0.85	2.73	1.03
	outdoor	2.40	0.91	2.67	1.05	2.40	1.18	2.13	0.83	2.53	1.13	2.07	0.70	2.87	1.06	2.80	1.01
Gaussian Splat	indoor	3.13	1.19	3.07	0.88	2.93	0.80	2.80	1.15	3.80	0.94	3.47	0.99	3.20	0.94	2.87	0.83
	outdoor	2.80	1.08	2.40	1.12	2.13	1.25	2.47	1.13	3.33	1.35	2.73	1.03	2.33	0.93	2.73	1.10

Table 4: Comparison of average ratings (Mean) and standard deviations (SD) regarding aspects of the environments’ creative impact for the different types and settings given on a Likert scale from 1 (low agreement) to 5 (high agreement).

Environment Type	Setting	Engagement		Exploration		Vision		Creativity		Satisfaction	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Depth Mesh	indoor	2.27	1.10	1.47	0.52	1.73	0.88	1.87	0.99	1.73	0.96
	outdoor	2.40	1.18	1.93	1.03	2.53	1.19	2.13	0.99	2.47	1.25
Blockade 3D	indoor	2.53	0.92	2.40	0.91	2.40	0.83	2.53	1.25	2.33	0.72
	outdoor	3.00	0.93	2.73	0.96	2.87	0.92	3.07	1.33	2.87	1.19
Gaussian Splat	indoor	3.40	1.06	3.33	1.11	3.40	0.74	3.53	1.19	3.27	0.96
	outdoor	3.07	0.96	3.00	0.93	2.80	0.94	3.13	1.15	2.47	0.99

Table 5: Comparison of average ratings (Mean) and standard deviations (SD) regarding the environments’ usefulness in different production steps for the different types and settings given on a Likert scale from 1 (low) to 5 (high).

Environment Type	Setting	Moodboard/ Ideation/ Concept		Storyboard/ Animatics (Lo-Fi)		Previs (Hi-Fi)		Techvis/ Set-Test		Final Production	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Depth Mesh	indoor	3.07	1.67	2.73	1.33	2.27	1.16	1.93	1.39	1.87	1.13
	outdoor	3.07	1.58	2.87	1.41	2.40	1.40	1.93	1.16	1.60	0.91
Blockade 3D	indoor	3.20	1.32	2.93	1.10	2.27	1.10	1.93	1.16	1.80	1.21
	outdoor	3.60	1.18	3.33	1.05	2.53	1.19	2.07	1.03	1.73	1.10
Gaussian Splat	indoor	3.93	1.10	4.00	1.07	3.73	1.28	3.20	1.42	2.27	1.44
	outdoor	3.33	1.29	3.33	1.23	3.00	1.46	2.80	1.61	1.80	1.27

Table 6: Comparison of average ratings (Mean) and standard deviations (SD) regarding the environments’ usefulness in different areas of application for the different types and settings given on a Likert scale from 1 (low) to 5 (high).

Environment Type	Setting	Virtual Production		Fully Digital Production		Television Sets		Web- Formats		Live Performances/ Events		High-End Productions		Amateur/Indie Productions	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Depth Mesh	indoor	1.93	0.96	1.93	1.16	1.93	1.16	2.53	1.06	2.27	1.03	1.53	0.74	2.40	1.06
	outdoor	2.13	1.06	2.20	1.21	1.93	1.39	2.80	1.26	2.40	1.30	1.53	0.92	2.60	1.24
Blockade 3D	indoor	2.27	0.96	2.27	1.16	2.20	1.41	2.73	1.28	2.40	1.24	1.80	1.01	2.80	1.21
	outdoor	2.13	0.83	2.40	1.18	1.80	1.08	2.73	1.16	2.53	0.99	1.60	0.99	2.87	1.06
Gaussian Splat	indoor	2.60	1.30	2.60	1.30	2.60	1.35	3.27	1.22	2.87	1.41	2.27	1.67	3.27	1.39
	outdoor	2.53	1.36	2.07	1.16	2.27	1.49	2.80	1.26	2.60	1.35	1.87	1.13	3.00	1.25

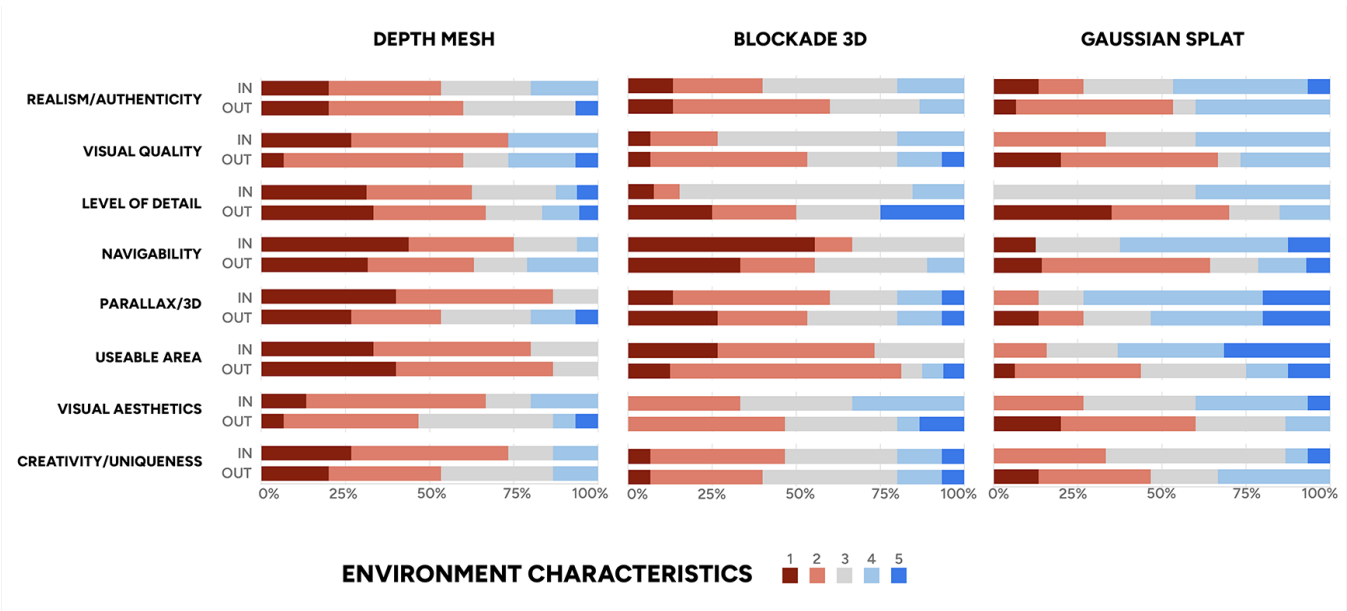


Figure 10: Stacked bar charts illustrating user ratings regarding environment characteristics per environment type on a Likert scale; red hues indicate low ratings, light grey neutral ones, blue positive ones.

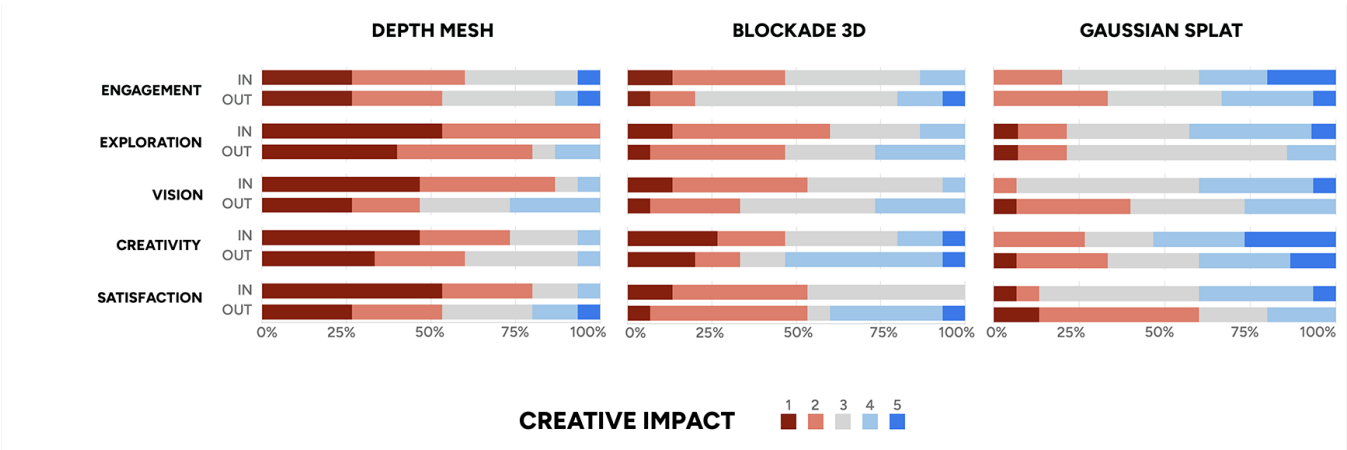


Figure 11: Stacked bar charts illustrating user ratings regarding creative impact per environment type on a Likert scale; red hues indicate low ratings, light grey neutral ones, blue positive ones.

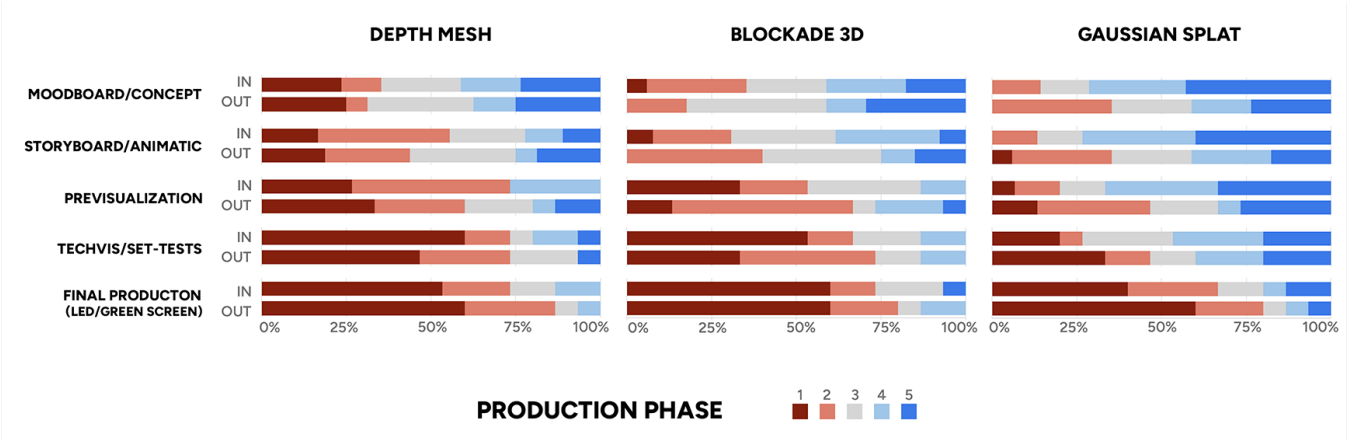


Figure 12: Stacked bar charts illustrating user ratings regarding production phase usefulness per environment type on a Likert scale; red hues indicate low ratings, light grey neutral ones, blue positive ones.

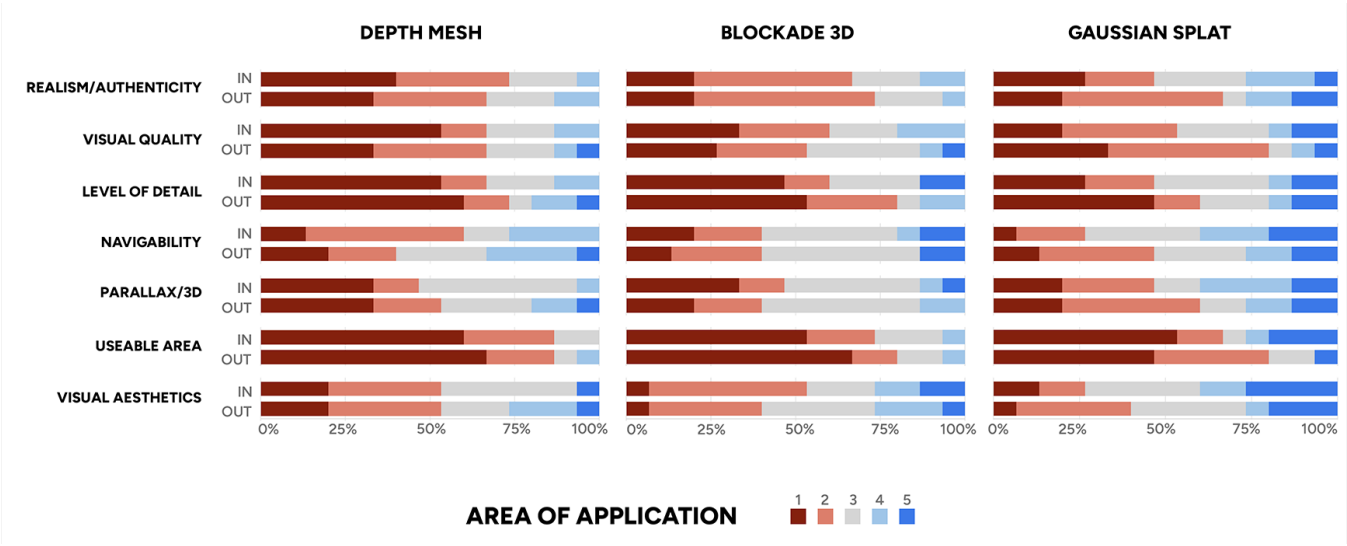


Figure 13: Stacked bar charts illustrating user ratings regarding general areas of application per environment type on a Likert scale; red hues indicate low ratings, light grey neutral ones, blue positive ones.