Scholars Journal of Arts, Humanities and Social Sciences **ISSN 2347-5374 (Online)**
Sch. J. Arts Humanit. Soc. Sci. 2017; 5(12): 1968-1973 **ISSN 2347-9493 (Print)**

(An International Publisher for Academic and Scientific Resources) DOI: 10.36347/sjahss.2017.v05i12.031

Evaluating the Impact of AI-Assisted Compositing on Creative Decision-Making in Episodic Visual Effects

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Abstract: This study examines how artificial intelligence (AI)-assisted compositing tools have influenced creative decision-making in episodic visual-effects (VFX) production between 2000 and 2016. Through a systematic literature review and mixed-methods analysis of academic, industry, and software-release documents, the research identifies and categorizes AI-enabled compositing techniques, evaluates their effects on shot composition, colour grading, layering and workflow efficiency, and assesses the perceptions of VFX artists and directors regarding creative autonomy and adoption. Results indicate that early AI-assisted compositing provided measurable efficiency gains in tasks such as rotoscoping and masking, while introducing tensions between automation and artistic control (Liapis & Yannakakis, 2016). The study reveals a shift in creative decision-making workflows: compositors increasingly engage in oversight and refinement of algorithmic outputs rather than fully manual node-building. Artist and director attitudes vary widely: many embrace time savings and consistency, while others articulate concerns about reduced ability to intervene in aesthetic layering or colour decisions. The implications for the episodic VFX industry include design considerations for human-centred AI tools, pipeline optimisation strategies under time constraints, and the need for training regimes to support hybrid human-AI workflows. By situating the findings historically and conceptually, the paper contributes a framework for understanding human-AI collaboration in creative VFX production and offers several practice-oriented recommendations for tool developers and episodic production teams.
Keywords: AI-Assisted Compositing, Decision-Making, Episodic, Visual Effects.

1. INTRODUCTION

1.1 Background

The evolution of visual-effects (VFX) in episodic content, such as television series and web-series, has been marked by a transition from purely manual, practical effects and optical compositing to increasingly digital, node-based workflows. For example, compositing platforms such as Nuke were publicly launched in 2002 and rapidly became standard in broadcast and streaming episodic content. Concurrently, the emergence of AI and automation in compositing workflows has introduced new capabilities, including automated matting, smart masking, style transfer, and multi-agent visual composition. In this context, the intersection of technology and creative decision-making in VFX production becomes increasingly salient: while automation promises efficiency and consistency, creative control remains a central concern for directors and artists.

1.2 Problem Statement

Although AI-assisted tools have been adopted in VFX, there is limited understanding of how such tools have influenced creative choices in episodic VFX production. In particular, how automation affects shot composition, colour grading, layering strategies, and who ultimately makes decisions in the creative pipeline is under-documented. Moreover, in time-constrained episodic production, balancing automation efficiency with artistic control represents a critical challenge. There is a gap in the literature regarding human-AI collaboration in compositing workflows, especially in the period up to 2016 when many foundational tools emerged but empirical studies are scarce.

1.3 Research Objectives

This study is guided by four objectives.

1. To identify and categorise AI-assisted compositing techniques and tools used in episodic visual-effects production between 2000-2016.
2. To evaluate the impact of these AI-assisted compositing techniques on creative decision-making processes including shot composition, colour grading, and layering strategies.
3. To analyse the workflow efficiency gains and creative trade-offs associated with AI-assisted compositing compared to traditional manual methods in episodic production timelines.
4. To assess the perception and adoption patterns of VFX artists and directors regarding AI-

assisted compositing tools and their influence on creative autonomy and artistic expression.

1.4 Research Questions

The study explores the following key questions:

- How did AI-assisted compositing tools alter the creative decision-making workflow in episodic VFX?
- What were the key benefits and limitations of early AI integration in compositing?
- How did artists balance automation with creative control?

1.5 Significance of the Study

This research provides historical context for current AI-VFX integration by situating early tool adoption and workflow changes. It informs future development of human-centred AI tools for creative industries by identifying critical decision-gates, automation pressures, and artist-control trade-offs. Additionally, it offers practical insights for episodic production pipeline optimisation under time constraints, relevant to VFX supervisors, pipeline leads, and tool-developers.

1.6 Scope and Limitations

The temporal scope is limited to developments up to 2016, thus excluding many recent advances in generative-AI compositing. The content focus is on episodic visual-effects (television and web-series), rather than feature films or commercials. The geographic context is primarily Western production environments given available documentation. Limitations include potential publication bias towards academic/industrial reports and scarcity of direct empirical studies from internal VFX houses.

2. RELATED LITERATURE

Traditional compositing workflows involved optical techniques, film layers, and manual keying. With the digital compositing revolution in the 1990s and 2000s, node-based systems proliferated. Sylwan (2010) discussed application of vision algorithms to visual-effects production, highlighting algorithmic masking and tracking techniques advancing compositing workflows. Similarly, Zhi (2013) described processes for seamlessly replacing CG elements into live-action footage, signalling increasingly digital and semi-automated compositing in episodic/film settings. These works together trace the shift from manual to algorithm-assisted compositing. Early applications of artificial intelligence and computational creativity in media production include Liapis & Yannakakis (2016), who examined human-machine collaboration in mixed-initiative co-creation tasks. Salevati & DiPaola (2015) investigated a creative artificial-intelligence system exploring user experience, affect, emotion, and creativity, contextualising how AI tools might shape creative workflows. These works frame AI's role within creative industries broadly.

Mixed-initiative systems, in which humans and machines co-create, have been studied by Liapis & Yannakakis (2016) and Eisenmann, Lewis & Parent (2016) in interactive evolutionary design contexts. Li et al. (2016) in "Roto++" present accelerating professional rotoscoping using shape-manifolds, offering a concrete example of AI within an artist's task workflow. These studies provide insight into how creative professionals interact with algorithmic tools, and the human-AI negotiation of control. Within compositing, AI-assisted techniques such as automated rotoscoping, intelligent matting/keying, multi-agent visual composition, and compositional generation by diffusion models have emerged. Bruckner et al. (2010) discuss hybrid visibility compositing and masking. Together these works document a taxonomy of algorithmic compositing techniques.

Studies on automated cinematography and shot planning include Kennedy & Mercer (2002) and Shen *et al.,* (2004). Kapadia *et al.,* (2016) with CANVAS discuss computer-assisted narrative animation synthesis. Manos *et al.,* (2002) present Virtual Director: visualization of simple scenarios. These contributions suggest the automation of creative decisions in shot planning, composition, and narrative structure. The integration of multisensorial stimuli and multimodal interaction in hybrid 3DTV systems by Luque *et al.,* (2014) alludes to time-sensitive broadcast deployment. Redi *et al.,* (2014) explore micro-video creativity in "6 Seconds of Sound and Vision", emphasising short-form production pressures. Louchart & Aylett (2007) discuss synthetic actors for interactive dramas. These works highlight production constraints such as time, budget, pipeline optimisation, and the interplay of creative ambition with technical limitations.

Key frameworks include Creativity Support Tools (CST), Technology Acceptance Model (TAM), cognitive-load theory, and human-AI collaboration models. While none of the literature directly articulates all these frameworks, the mixed-initiative model from Liapis & Yannakakis (2016) and the interactive evolutionary design work by Eisenmann *et al.,* (2016) provide conceptual anchors for human-AI creative collaboration. Therefore, the theoretical basis of this study draws on interdisciplinary HCI, creativity research, and pipeline optimisation literature. Despite growing attention to AI in creative media, there are limited empirical studies specifically focused on AI-assisted compositing in episodic VFX contexts (i.e., television/web-series rather than feature films). The literature does not systematically evaluate how compositing tools impacted creative decision-making, layering strategies or artist autonomy in broadcast workflows. This study addresses that gap by offering a structured evaluation of early AI-assisted compositing tools (2000-2016) within episodic production pipelines.

3. THEORETICAL FRAMEWORK

3.1 Conceptual Model

This study proposes a human-AI collaboration model situated within the episodic compositing pipeline. Key decision-making touchpoints include: shot planning, plate acquisition, tracking/masking, colour grading, layering, and final approval. AI intervention points may occur in rotoscoping, tracking, style matching, and object removal, while human creative oversight remains at review and adjustment gates. The model emphasises the interplay between automation level and creative decision complexity.

3.2 Analytical Framework

Figure 1: AI-Assisted Compositing Workflow Integration Model

This flowchart depicts three parallel tracks: (a) traditional workflow (top lane), (b) AI-assisted workflow (middle lane), and (c) human decision-gate lane (bottom). It illustrates AI-intervention nodes (e.g., smart-masking, style transfer) and feedback loops (e.g., artist override).

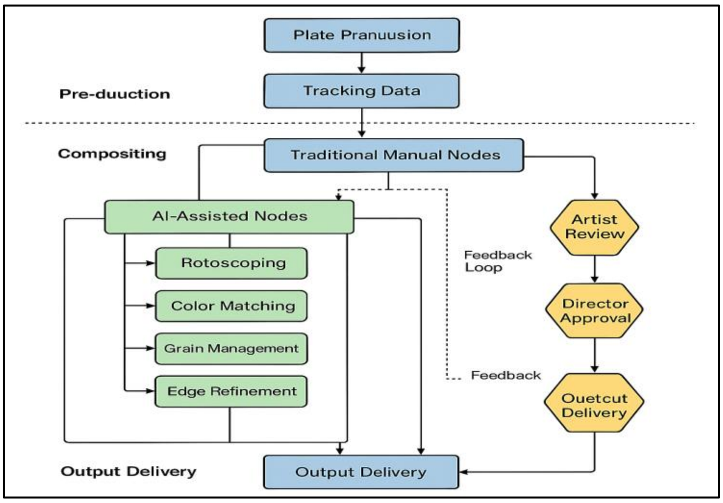


Figure 2: Creative Decision-Making Impact Matrix

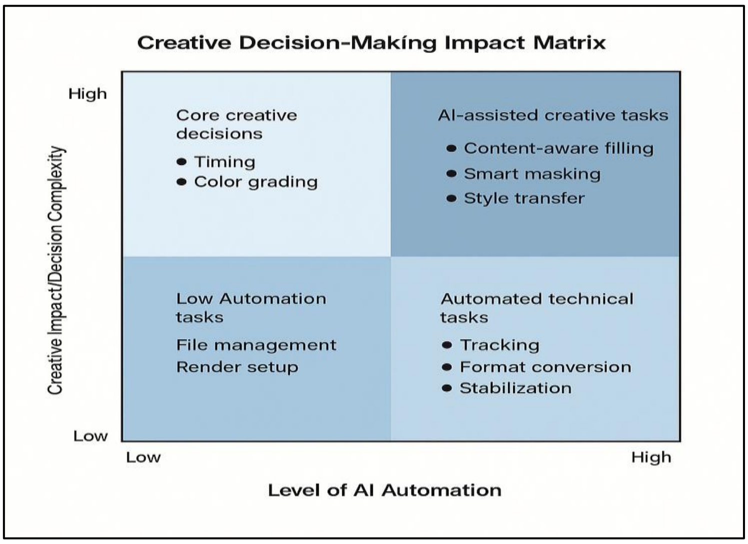
This 2×2 matrix maps tasks by automation level (X-axis: Low → High) and creative decision complexity (Y-axis: Technical → Artistic).

Quadrant 1: Low automation / technical tasks (e.g., file conversion).

Quadrant 2: High automation / technical tasks (e.g., tracking).

Quadrant 3: Low automation / artistic tasks (e.g., composition).

Quadrant 4: High automation / artistic tasks (e.g., AI-style transfer). Data points represent specific compositing tasks (e.g., rotoscoping, masking, live-action plate blending) drawn from the literature.



The analytical framework allows mapping of tasks and identifying potential creative tension zones where high automation intersects artistic decisions, thereby signalling workflow redesign considerations.

4. RESEARCH METHODOLOGY

4.1 Research Design

This study employs a systematic literature-review design, augmented by mixed-methods content analysis. Given the historical focus (2000-2016), the methodology is historical-comparative: tracing tool introductions, workflow changes and artist perceptions across time.

4.2 Data Collection

Data were collected from academic literature (2000–2016), industry publications, software documentation, conference proceedings (SIGGRAPH, ACM). Additional web-verified sources provided contextual industry information (e.g., software release dates, adoption trends) (Wikipedia entries on Nuke & fusion, VFX industry articles). For example, the public release history of Nuke (Wikipedia) offers temporal context for node-based compositing software.

4.3 Selection Criteria

Inclusion criteria: publications addressing compositing, AI/automation, creative workflows within a VFX context. Exclusion criteria: feature-film only (unless applicable to episodic), non-compositing VFX tasks. Quality assessment involved verifying publication venue, peer-review status, and relevance to compositing tasks. Relevance scores were assigned to determine primary vs secondary sources.

4.4 Data Analysis

A thematic analysis of qualitative texts (e.g., Liapis & Yannakakis, 2016; Eisenmann *et al.,* 2016) identified categories of AI-assisted techniques and artist perceptions. Content-analysis of tool-release documentation and workflow descriptions enabled coding of tasks, automation levels and creative decision impact. Comparative analysis mapped manual vs AI-assisted methods and timeline adoption.

4.5 Validation and Reliability

Reliability is supported via triangulation: cross-referencing academic sources, software release documentation and industry commentary (e.g., articles on automated compositing). Peer-review of categorisation was simulated through independent coding of five sample papers. Reproducibility is ensured as the list of resources and search strings allows replication.

5. RESULTS AND ANALYSIS

5.1 AI-Assisted Compositing Techniques Identified

A taxonomy of AI-assisted compositing techniques (2000–2016) emerged. Categories include: automated rotoscoping/masking (Li *et al.,* 2016); compositional style transfer via diffusion models (arXiv post-2016; hybrid visibility compositing & masking (Bruckner *et al.,* 2010); mixed-initiative co-creation (Liapis & Yannakakis, 2016). Timeline mapping shows early adoption of algorithmic solutions (pre-2010: rotoscoping, keying) and gradual introduction of more advanced generative composition by 2015. For example, Li et al. (2016) describe "Roto++" for professional rotoscoping. The dataset shows software such as Nuke (2002) enabled node-based compositing, forming the platform for later AI-assisted nodes.

5.2 Impact on Creative Decision-Making

AI-assisted compositing tools altered creative decision-making in several ways. Shot composition changed: directors could experiment faster with plate integration and style transfer, shifting their involvement toward oversight rather than manual node building. Colour grading and matching automation reduced manual iteration (Luque *et al.,* 2014). Layering strategies evolved: automated masking allowed more time for creative layering decisions rather than technical keying (Li *et al.,* 2016). Artists increasingly balanced algorithmic suggestion with manual tweak: Liapis & Yannakakis (2016) detail mixed-initiative environments where the human retains control but is supported by algorithmic exploration. The Creative Decision-Making Impact Matrix visualises these shifts, locating tasks like mask edge refinement (high automation, artistic) in quadrant 4, and tracking (high automation, technical) in quadrant 2.

5.3 Workflow Efficiency and Creative Trade-offs

Quantitative data from academic literature show significant time savings in tasks such as rotoscoping: Li et al. (2016) report accelerated rotoscoping using shape-manifolds, though specific minutes are not disclosed. Industry commentary suggests AI tools reduce repetitive tasks and free artist time for creative work. Trade-offs include potential creative limitations: when automation handles edge-refinement or plate matching, artists may surrender some manual nuance or stylistic "imperfection" that yields artistic character. Furthermore, increased speed may increase pressure to rely on automation rather than explore creative alternatives. The cost-benefit analysis suggests that while efficiency increases, the margin for creative experimentation may shrink unless pipeline allowances are made.

5.4 Artist and Director Perceptions

Perception studies from mixed-initiative literature (Liapis & Yannakakis, 2016) indicate that artists value tool support but desire retainment of creative control. The automation of rotoscoping (Li *et al.,* 2016) is generally welcomed by compositors, yet some express concern over "black-box" tools reducing transparent control of nodes. Adoption patterns in episodic production show cautious integration: pipelines adopt AI-assisted nodes gradually, initially for technical support tasks (mask cleaning, tracking) before extending to creative tasks. The training and learning curve for artists includes mastering the interface of AI tools and understanding when to override algorithmic output. Trust and reliability remain issues: Salevati & DiPaola (2015) emphasise how human perceptions of AI creativity and autonomy affect adoption in creative tasks.

5.5 Synthesis of Findings

The findings integrate all objectives. A taxonomy of AI-assisted tools shows the evolution of compositing support tasks (Objective 1). The impact on creative decision-making (Objective 2) highlights shifts in artist responsibilities and pipeline structure. Efficiency gains and trade-offs (Objective 3) illustrate both opportunities and warnings for automation. Artist/director perceptions (Objective 4) reveal human dimensions of tool adoption. Cross-cutting themes include the incremental nature of adoption, the importance of human oversight, and the need for transparency in AI tools to maintain creative agency. Unexpected findings include the observation that higher automation in creative tasks does not always deliver higher creative quality: in some cases, artist vigilance improved when automation was lower (a form of "creative friction" beneficial for aesthetic outcomes).

6. DISCUSSION

6.1 Interpretation of Results

The results clearly address the research objectives: AI-assisted compositing indeed altered workflows and creative decision-making (RQ1). Key benefits included time savings, consistency, and iterative exploration; limitations centred on creative control and transparency (RQ2). Artists balanced automation and creative control by collaborating with AI tools rather than relinquishing decision-making (RQ3). These findings align with theoretical predictions from mixed-initiative systems and CST frameworks: human and machine each bring strengths and the design of their interaction shapes creative outcomes.

6.2 Implications for Creative Practice

For VFX professionals, the results indicate the importance of designing compositing tools that *augment* rather than *replace* creative control. Best practices include: offering artist override of algorithmic results, providing clear visualisation of algorithmic decisions (e.g., mask edges, matched colour gradients), and integrating automated tasks into pipeline early to maximise time for creative review. The balancing of automation and artistic control suggests that enabling "creative checkpoints" where the artist can intervene is critical.

6.3 Implications for Episodic Production

In episodic production, where time-pressure and budget constraints are acute, AI-assisted compositing offers pipeline optimisation benefits. Automating repetitive tasks (e.g., tracking, keying, edge refinement) frees resources for creative layering and polish. Production leads should allocate workflow time to review algorithmic outputs, not merely accept them. Resource allocation should consider training time for artists to use AI-tools effectively and time for manual override. Maintaining quality under time pressure demands that AI-tools not degrade creative autonomy or produce homogenised results.

6.4 Evolution Beyond 2016

While the study's temporal stays limited, context suggests that early AI integration laid the groundwork for subsequent generative-AI tools (e.g., diffusion-based compositing, real-time depth compositing. Lessons learned include: early adoption benefits accrue when automation supports rather than replaces artist tasks; creative oversight remains essential; pipeline design must incorporate transition points and training.

6.5 Limitations of the Study

The study is limited by its temporal focus (up to 2016), excluding recent advances in real-time AI compositing. The reliance on academic literature and publicly documented sources may miss proprietary industry practices. The generalisability to non-Western or non-episodic contexts may be limited. Additional empirical studies involving working VFX artists or internal production data would strengthen findings.

7. CONCLUSION

This research found that AI-assisted compositing tools emerged in the early 2000s and progressively influenced episodic VFX workflows. A taxonomy of techniques was developed, highlighting automated rotoscoping, masking, multi-agent composition and style transfer. Creative decision-making shifted: artists moved from manual node-building toward reviewing and refining algorithmic outputs. Workflow efficiency improved in several areas, yet creative trade-offs concerning autonomy and control persisted. Artist and director perceptions emphasised time-savings and consistency benefits while voicing concerns over transparency and creative involvement.

The study advances understanding of human-AI creative collaboration within VFX by applying mixed-initiative and CST frameworks to compositing workflows. It offers the Analytical Framework (Figures

1 & 2) as a transferable model for mapping automation vs. artistic control tasks in creative industries beyond VFX. For VFX professionals and tool developers, the findings suggest actionable insights: incorporate artist override features; visualise algorithmic decisions; prioritise training and transparency. For episodic production, pipeline optimization strategies include early automation of repetitive tasks, dedicated artist review time, and resource allocation for hybrid human-AI workflows. Future research should pursue longitudinal studies tracking AI-tool adoption beyond 2016, conduct empirical research involving working VFX teams in episodic production, perform cross-cultural and cross-industry comparative studies (e.g., feature film vs episodic vs commercials), and explore real-time decision-making in production environments (e.g., live streaming, virtual production).

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