Universal Library of Engineering Technology Research Article

ISSN: 3064-996X | Volume 3, Issue 3

Open Access | PP: 101-109

DOI: https://doi.org/10.70315/uloap.ulete.2026.0303015

Artificial Intelligence in Animation Production: Transformation of Production Processes, Management, and Professional Work

Nikolai Khudiakov

Entrepreneur and Organizer with Experience in Creating Educational and Professional Projects within the Fields of Animation and Production.
Former CEO of Animation School.

Abstract

Generative and assistive artificial intelligence (AI) is reshaping how animated content is planned, produced, and managed. This article examines how AI changes production processes, production management, and professional work in animation. The study combines a structured review of 20 sources published between 2023 and 2026, a comparative analysis of stage-level adoption data, and a case study of the author's practice in animation education and production. Sources were classified by type and synthesized across the production pipeline and its management and workforce dimensions. Reported adoption is higher in ideation-heavy stages, such as storyboarding and concept art, than in technically constrained stages, such as denoising and rigging assistance. Three original models are proposed: a hybrid pipeline with human approval gates, a task-allocation framework, and a studio-school co-production loop. Productivity gains appear to depend on where human review is placed in the pipeline and how quality is controlled, not on tool capability alone. The article is intended for studio producers, animation educators, policy makers, and clients who commission animated content.

Keywords: *Animation Production, Generative Artificial Intelligence, Production Management, Creative Labor, Animation Education, Human-In-The-Loop Systems, Creative Industries, Hybrid Pipeline, Workforce Development.*

INTRODUCTION

Animation is a sequential and labor-intensive form of production. A finished sequence passes through scripting, storyboarding, layout, animation, rigging, rendering, compositing, and review, and each handoff carries cost, schedule, and quality risk. Generative AI has entered this chain quickly. A bibliometric review of generative AI and the creative industries maps a research field that has grown in recent years [4]. Practitioner-reported evidence shows that adoption is already present in some stages: reported use reaches 45.6% for storyboarding and 41.6% for concept art, compared with 16.0% for rigging assistance and 10.4% for denoising [14]. These figures describe perceptions rather than measured output, but they show that AI use in animation is uneven across the pipeline.

Three concepts organize the analysis. The production pipeline is the ordered set of stages through which a shot or sequence passes, from pre-production to delivery. Production management refers to the decisions that allocate people, time, budget, and quality control across that pipeline. Professional work refers to the roles, skills, and career paths of the people who carry out and supervise the tasks. AI affects each concept differently. It changes the pipeline by shifting where effort is spent, it changes management by altering the cost structure and the points at which decisions are made, and it changes professional work by moving some tasks from execution to specification and review.

In this context, a human-in-the-loop system is one in which a person holds the decision at defined points, rather than only supervising a process that runs without intervention. The distinction matters because it determines where responsibility sits. The hybrid pipeline examined in this article is a specific form of human-in-the-loop organization, in which each AI output is reviewed before it enters the next stage [14].

Work on practitioner adoption describes hybrid arrangements, in which AI generates options and people control approval, as a likely shape for the next phase of production [14]. Multidisciplinary research agendas for generative conversational AI call for work that connects the technology with practice and policy [9]. Industry forecasts point in the same direction, although they also describe a

Citation: Nikolai Khudiakov, "Artificial Intelligence in Animation Production: Transformation of Production Processes, Management, and Professional Work", Universal Library of Engineering Technology, 2026; 3(3): 101-109. DOI: https://doi.org/10.70315/uloap.ulete.2026.0303015.

cautious approach by studios toward generative content creation [7]. Consulting surveys report that organizations across sectors now use AI in at least one business function [15], which suggests that the questions raised here are not confined to a single market.

Existing research has mapped several parts of this change. Reviews of cinematographic production, cel animation, and film creation catalog technical methods for planning and generation [3, 19, 20]. Earlier work addresses AI in digital video production [17] and in film production [18]. Studies outside animation show that generative tools can shorten task completion and raise rated quality in professional writing [16], and that productivity gains tend to be larger for less experienced workers [5]. Other work reports that AI assistance can raise individual creativity while reducing the collective diversity of novel content [8], and that the value and authorship of AI-assisted art remain open questions [10]. Broad systematic reviews map generative AI applications across domains [11], but few of them link stage-level adoption to management decisions or to professional training in animation.

The research gap is therefore twofold. First, the evidence on AI adoption in animation is stage-specific and perception-based, so it does not show how adoption changes the way a production is managed. Second, the education literature addresses prompt literacy and generative AI readiness [13], but these workforce consequences are not yet tied to the roles and handoffs of a particular production pipeline.

The aim of this study is to examine how AI changes animation production processes, production management, and professional work, and to propose operational models that studios and educational institutions can apply. The study addresses three questions: how AI adoption varies across production stages; how production management and quality control change when AI enters the pipeline; and what these changes mean for professional roles and training.

The novelty of this study lies in linking stage-level adoption evidence, management decisions, and workforce development within a single analytical framework that is applied to a practice-based case.

Based on the reviewed evidence and the author's practice, the study examines the following hypothesis. H1: When AI outputs pass through defined human review gates, AI integration shortens stage cycle time without a loss of perceived artistic quality, whereas AI use without formal gates produces rework that offsets part of the gain.

The study has several limitations. The evidence base consists of 20 sources selected through a structured review, so it is illustrative rather than exhaustive. The adoption figures come from practitioner perceptions and are not measured production outcomes, and the efficiency evidence for animation rests on a small sample of ten cases [6]. The case material relies on the author's organizational records, which have not been independently verified and which reflect one practitioner's position. Tool capabilities change faster than peer-reviewed publication cycles, so specific technical claims may age quickly. The treatment of management and workforce effects is qualitative. These limitations do not undermine the proposed models, but they mean that the hypothesis needs confirmation through controlled studies in studios.

The study is relevant to two audiences. For US clients, including animation studios, streaming and advertising producers, game developers, and vendors of production software, the proposed pipeline and decision framework offer a way to staff review roles, price AI-assisted work, and document human authorship. For the author's home country, the findings bear on how animation talent is trained and placed. Animation education that works directly with production companies can prepare graduates for studio roles and can adjust curricula to the review and supervision tasks that AI creates. The author's experience of founding an animation school, directing an industry festival, and developing a training model implemented with a production group in three countries illustrates how a professional community with practical training can contribute to national production capacity.

MATERIALS AND METHODS

The study uses a qualitative, comparative design with three components. The first is a structured review of peer-reviewed and consulting sources on AI in creative production, animation, film, and creative labor. The second is a comparative analysis that places the stage-level adoption data [14] alongside technical and organizational findings [6, 19, 20]. The third is a single-case study of the author's practice in animation education and studio-school co-production. Case studies suit process questions in which the context of practice matters. The single-case design is used here to generate and illustrate models, not to test them statistically.

Sources were eligible if they were published between January 2020 and July 2026, addressed AI in creative production, animation, film, visual media, or creative management and labor, and appeared either in a peer-reviewed venue or in a consulting report from a recognized firm. Blogs, press releases, news items, vendor pages, and aggregated market estimates without a traceable method were excluded, because their figures could not be checked against an origin. The final set contains 20 items: 18 peer-reviewed works and 2 consulting reports. This gives a peer-reviewed share of 90% and a consulting share of 10%.

The case material includes the number of graduates of an animation school in which the author served as founder and chief executive officer from 2016 to 2023, the annual participation in the Animators' Gathering festival (Слет

аниматоров), the industry partners recorded by the festival, and the deployment of a training model developed with a production group in Russia, Turkey, and Uzbekistan. These data come from the author's organizational records. They are reported descriptively and are not treated as independent evidence.

RESULTS AND DISCUSSION

Figure 1 is used to show the gap in reported adoption between the early and the technical stages of production, because that gap is the starting point for the stage-level analysis that follows.

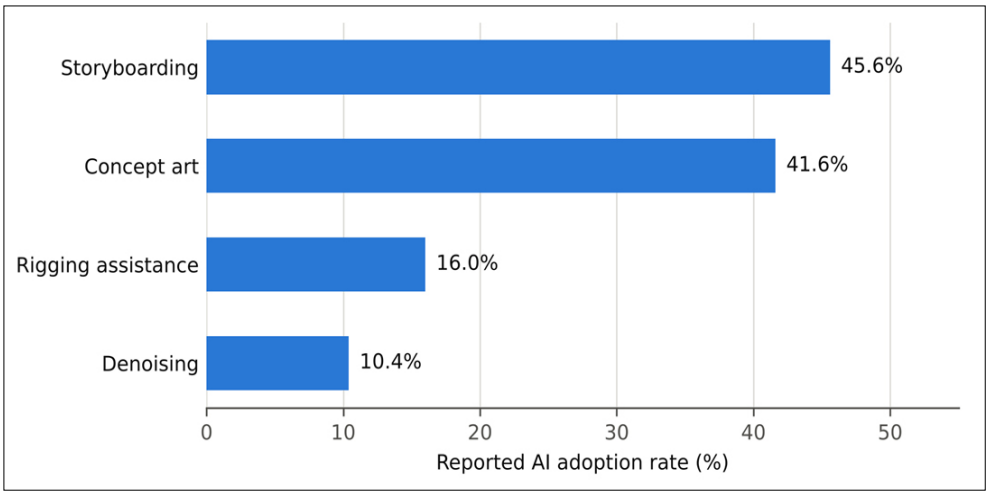


Figure 1. Practitioner-reported AI adoption rates by animation production stage (compiled by the author based on [14]).

The pattern in Figure 1 is consistent with the nature of the tasks. Storyboarding and concept art involve divergent generation, in which many candidate outputs are acceptable and the cost of an unsuitable draft is low. The generative systems surveyed for cel animation and film creation are oriented toward producing and exploring candidate visuals [19, 20]. Rigging assistance and denoising involve constrained, technical outputs in which errors propagate into later stages. Adoption is therefore lower where tolerance for error is lower and integration with existing software is more demanding. Table 1 links each stage to its adoption value, to the role the AI tool plays, and to the human gate that the synthesis recommends.

The concentration of adoption in early stages has a practical consequence for throughput. Early stages set the volume of work that flows downstream. AI-assisted ideation can increase the number of options that a team reviews, but it also increases the number of decisions that must be made before animation begins. If those decisions are not resourced, the bottleneck moves forward rather than disappearing. Technical stages reward automation that reduces repetitive labor, yet adoption there is lower. As an inference rather than a measured result, this suggests that integration with production software and technical standards is a limiting factor in those stages.

Table 1. Adoption values, AI role, and proposed human gate by production stage (compiled by the author based on [14, 19, 20]).

Production stage	Reported adoption (%)	Role of AI in the stage	Proposed human gate
Storyboarding	45.6	Draft frames and shot options	Director sign-off
Concept art	41.6	Generate style and variant options	Director sign-off
Rigging assistance	16.0	Suggest weight and skeleton setup	Lead animator edits
Denoising	10.4	Remove render noise and upscale frames	Technical check

Efficiency evidence for animation is limited but directionally clear. Chen et al. [6] apply network data envelopment analysis to multi-stage animation production and report that AI integration is associated with higher production efficiency. Their sample includes ten cases, and some stage descriptions in the paper are not fully consistent, so this article relies on the direction of the effect rather than on its magnitude. Evidence from other creative and knowledge work points the same way. In a controlled experiment with professional writing tasks, access to a generative model reduced completion time and increased rated quality [16]. In a field deployment with customer support agents, productivity gains were concentrated among less experienced workers [5], which suggests that AI may narrow the performance gap between junior and senior staff.

Network data envelopment analysis evaluates decision-making units that consist of linked sub-processes, so inefficiency can be located in a particular stage rather than only in the total output. This matters for animation, where a delay in one stage propagates to the next. The method therefore fits the question of where AI should be introduced. Chen et al. [6] apply it to a small set of production cases, and their study should be read as a structural illustration of how stage-level efficiency can be measured, not as an estimate that applies to the animation industry as a whole.

Efficiency is not the only dimension that matters. Doshi and Hauser [8] report that AI assistance raises individual creativity while reducing the collective diversity of novel content. For animation studios, whose value often rests on a distinct visual identity, this is a management risk. A faster pipeline that converges on similar styles can erode the value the studio sells. Haase and Hanel [12] report that chatbot outputs reach a level comparable to human creativity in the tests they describe, and Epstein et al. [10] discuss the need to evaluate AI-assisted art in terms of process, authorship, and social context. Taken together, these sources imply that efficiency and creative distinctiveness must be managed together.

Figure 2 is used to show where AI tools enter the pipeline and where human decisions must hold authority, because the integration model depends on that placement.

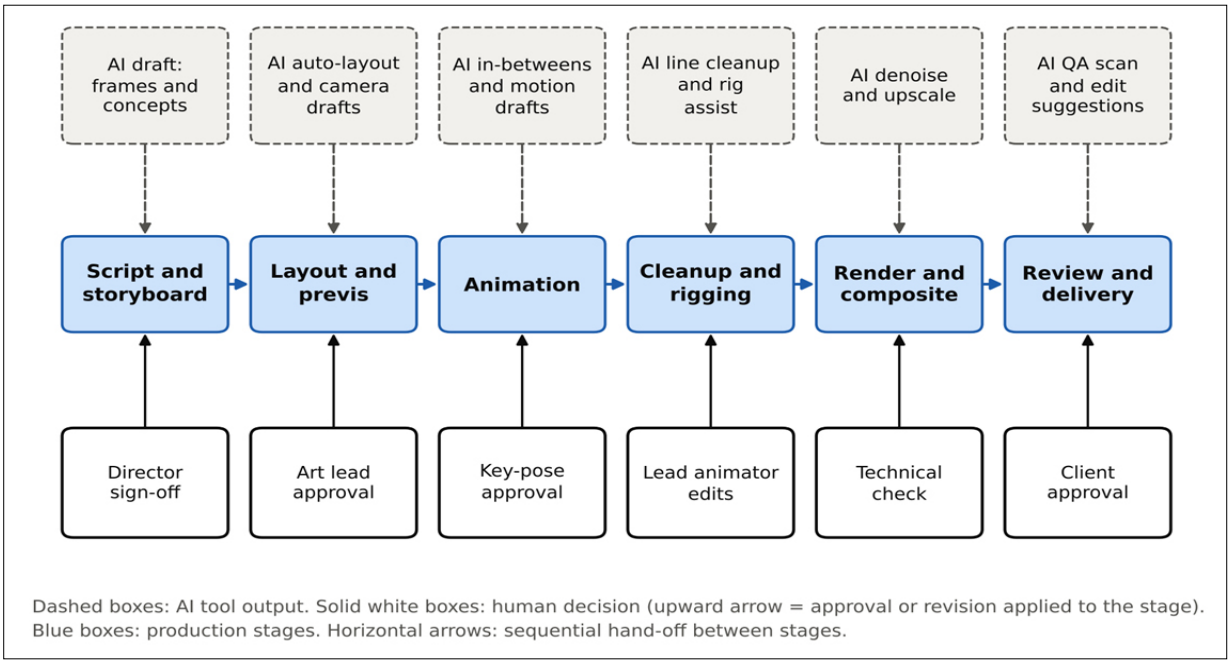


Figure 2. Hybrid AI-integrated animation pipeline with human approval gates (compiled by the author based on [1, 2, 14, 19]).

In the proposed pipeline, each stage receives an AI output and a human decision. The AI output is treated as a draft that is accepted, revised, or rejected at the gate. This structure follows the human-guided logic of the HGAI framework [14], in which practitioners retain decision authority over stage transitions. Gates also make the workflow auditable. A record of which output was generated, who approved it, and what was changed provides evidence of human authorship, which matters for rights questions and for client review. Amankwah-Amoah et al. [1] identify challenges that creative firms face when generative AI disrupts their industries, and a gate record offers a practical response to accountability challenges within a single studio.

Stage by stage, the pipeline assigns different authority to AI and to people. In script and storyboard, AI output is treated as a source of candidate ideas. The director's sign-off is the gate, and no AI-generated frame moves forward without it. In layout and previs, AI can propose camera positions and blocking variants, but the layout lead keeps responsibility for spatial logic and for the continuity of the scene.

In animation, AI-generated in-betweens and motion drafts can save considerable labor, so this stage carries a significant risk that unreviewed material enters later stages. The key-pose approval therefore sits before any in-between is generated, which keeps the performance and acting choices in human hands. In cleanup and rigging, AI line cleanup and rig assistance pass to the lead animator, who edits or rejects the result before it reaches the technical check.

Rendering and compositing rely on deterministic processes, such as denoising and upscaling, so the technical check can be a sampling check rather than a frame-by-frame review. Review and delivery combine AI-based quality scans with human judgment. The scans flag defects, but client approval remains the final decision, and the gate record shows which corrections were made in response to each flag.

Implementing the pipeline in a studio can follow four steps. The first is a pilot on a single sequence, chosen because its stages are representative and its deliverables are not time critical. The second is the definition of gates. For each stage, the team names the reviewer, states the criteria for acceptance, and sets a limit on revision rounds. The third is the training of reviewers, who need to recognize the typical failure modes of AI output and to explain their decisions in the gate record. The fourth is measurement. The studio records cycle time, rework, and gate rejections for each stage, then compares the

pilot with a comparable sequence produced without gates. Only after these steps does the studio extend the pipeline to further productions. This sequence treats the gate as the unit of adoption rather than the tool, which is consistent with the accountability and controllability criteria.

Figure 3 is used to turn the stage analysis into a decision rule that managers can apply to individual tasks. A single pipeline-wide policy would ignore the differences shown in Figure 1 and Table 1.

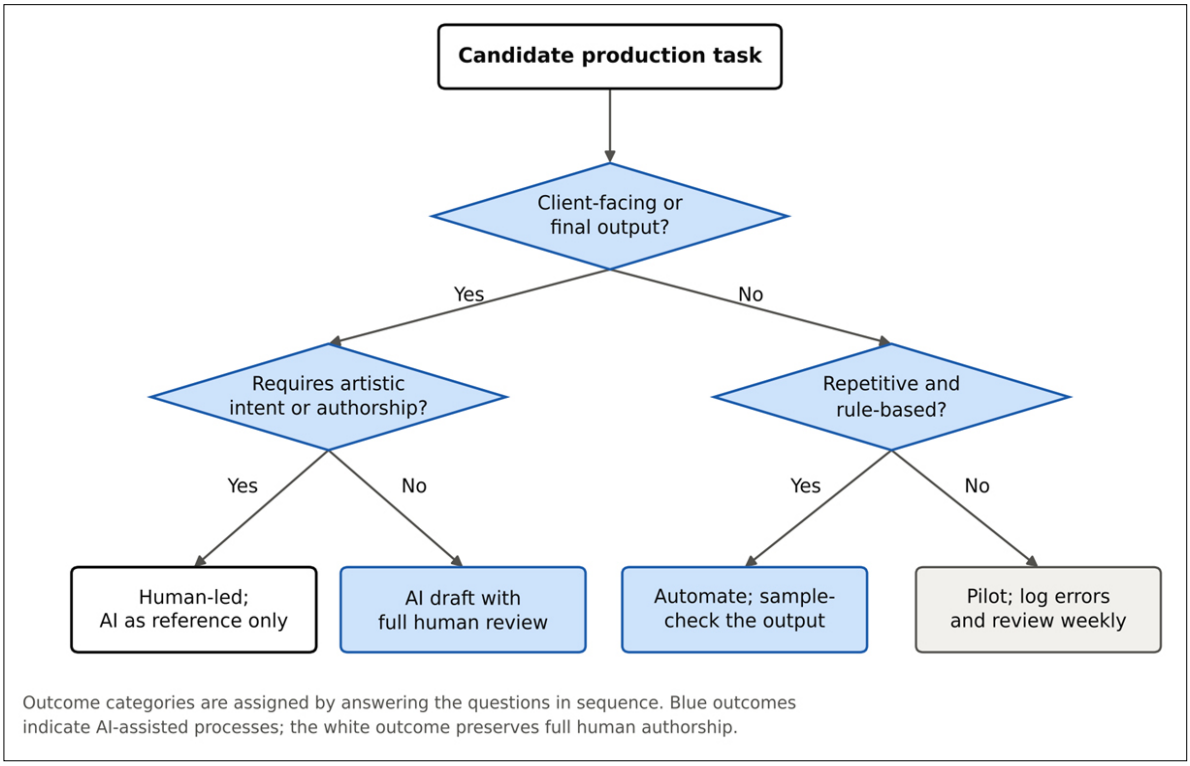


Figure 3. Task-allocation decision framework for AI use in animation production (compiled by the author based on [2, 3, 14]).

Figure 3 sorts tasks by three questions: whether the output is client-facing or final, whether the task requires artistic intent or authorship, and whether the task is repetitive and rule-based. The answers lead to four outcomes, and each outcome maps onto a management action. Management changes in three areas. Budgeting shifts from labor hours toward tool licensing, review time, and data governance, so estimates must count review hours explicitly. Scheduling must allow for approval queues, because a fast generator can move work into a bottleneck at the director or lead-animator stage. Quality control moves from inspecting finished frames toward checking gate criteria and sampling automated outputs. Automating repetitive tasks reduces the labor cost per unit, but it does not remove the need for periodic checks, since errors in automated outputs can pass unnoticed unless they are sampled. The fourth outcome, a pilot with logged review, applies to tasks that are neither client-facing nor repetitive. Such tasks are used to learn where AI helps, and the logged errors determine whether a task moves to a different outcome.

Management also faces risks that the stage analysis does not show. The first is excessive iteration. A generator that produces acceptable drafts quickly can encourage repeated revisions, which erode the time that was gained, so a fixed limit on revision rounds at each gate prevents this drift. The second is data governance. Production teams that use external tools must know which material is uploaded, where it is stored, and whether it may be used to train other systems. The third is client disclosure. Clients may ask how AI was used in a deliverable, and a gate record gives a direct answer. Amankwah-Amoah et al. [1] point to such challenges as organizational questions that a research agenda must address. This article treats them as governance tasks rather than as problems that a tool choice can resolve.

Pricing and contracting follow from the same logic. When review is a distinct and recorded activity, a vendor can separate the cost of generation from the cost of supervision, and a client can see what it pays for. Contracts can then specify the number of revision rounds at each gate, the reviewers responsible for approval, and the deliverables that carry a gate record. Such arrangements make disputes easier to resolve, because the record shows which decision was made, by whom, and at which stage. They also make the cost of rework visible, which can otherwise be hidden in general overhead when AI use is informal.

Several boundaries apply to the models. Figure 3 assumes that the three questions capture the main differences between tasks, but a task can be client-facing and rule-based at the same time, for example a standard turnaround for a short logo animation. In such cases the more restrictive answer should

govern. The gate structure in Figure 2 assumes that a studio can staff named reviewers for each stage. Smaller teams may combine roles, but the gate function should remain explicit even when one person holds several approvals, so that the record of human decisions does not disappear.

Quality control changes in two ways when AI enters the pipeline. The first is that checks move earlier, because a defect in an early draft can propagate through every later stage. The second is that checks must address new failure modes, such as drift in character design across shots, inconsistent lighting between generated frames, and artifacts that appear only in motion. A studio can address these failure modes with simple and repeatable checks. These include a reference sheet for each character, against which every AI-generated variant must be matched; a sampling plan for each stage, recorded in the gate record; and a periodic comparison of new work with the studio's archive of earlier productions.

The last check responds to the diversity concern raised by Doshi and Hauser [8]. When AI assistance converges on common outputs, a studio can measure that convergence by comparing new work with its own earlier work. The result can then inform whether a stage needs a stronger creative brief or a more restricted set of tools. Quality control therefore becomes a source of creative direction as well as a defect filter, which is why it belongs in the gate design rather than at the end of the pipeline.

Figure 4 is used to show how changes in professional work feed back into training, because the effect of AI on animators depends on what schools teach and what studios accept.

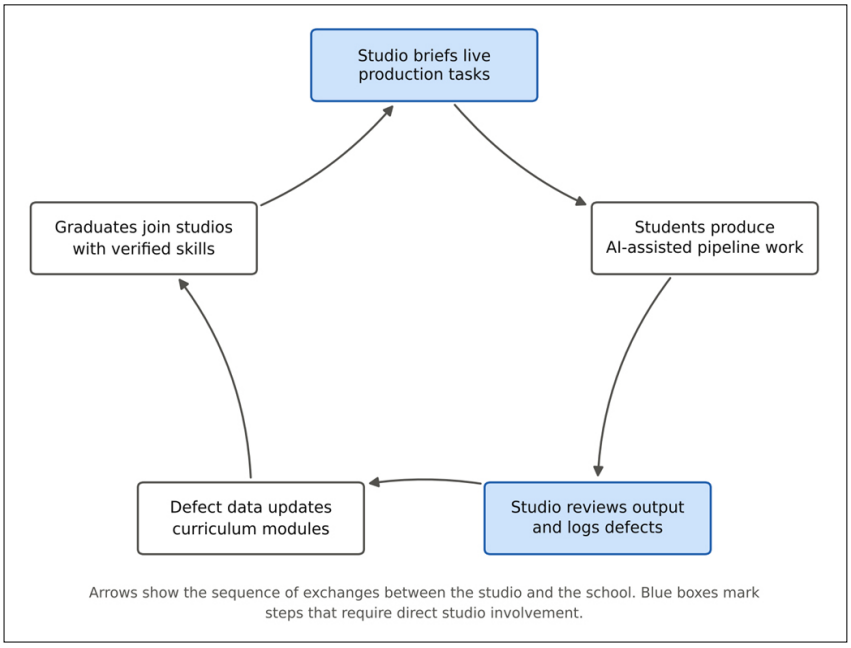


Figure 4. Studio-school co-production loop for AI-era animation training (compiled by the author based on [13] and on the case records summarized in Table 2).

Professional roles shift from producing every frame toward specifying, supervising, and checking machine-assisted output. The skills that matter include prompt literacy, an understanding of production constraints, and critical review. Loh et al. [13] examine prompt literacy and generative AI readiness among students in AI-assisted animation workflows, which supports treating these skills as explicit learning objectives rather than assumptions about students. Zhang et al. [20] survey generative film creation as a process that spans several production stages, which reinforces the need for review skills at each stage.

The roles that change are concentrated in junior and mid-level positions. Junior artists may spend less time on repetitive cleanup and more time on review, which can shorten the path from training to responsibility. The same change also removes some of the practice through which junior artists learn fundamentals. Training programs therefore need deliberate exercises in which students produce work without AI assistance, compare it with an AI-assisted version, and explain the difference. Such exercises preserve the craft knowledge on which gate decisions depend. The argument is consistent with the finding that productivity gains concentrate among less experienced workers [5], because the same gains could weaken the learning that builds senior judgment if training does not adjust.

Mentorship is the other side of professional change. In studios, junior staff learn largely by observing the decisions of senior artists during production. When AI drafts replace part of this observation, the mentoring relationship must be rebuilt around the gate. Senior artists can use the gate record as a teaching tool by reviewing with junior staff the reasons behind accepted and rejected outputs. This use turns a compliance artifact into a learning resource and helps preserve the judgment on which the review function depends.

A curriculum that prepares students for this environment can be organized around four modules. The first is pipeline literacy, which teaches students how a shot moves through the stages and where each handoff carries risk. The second is prompt and tool literacy, which covers how to specify a request, how to vary its parameters, and how to document what was asked. The third is review practice, in which students assess AI output against reference criteria and justify acceptance or rejection in writing. The fourth is attribution and ethics, which covers authorship records, disclosure to clients, and the treatment of licensed material. The modules are assessed with studio feedback, so that the curriculum follows the gate criteria that industry partners apply in practice. The design draws on the readiness findings in [13] and on the production-based training model that the author has implemented, and it should be evaluated before it is treated as a standard.

Table 2 summarizes the case metrics used to illustrate the loop. The table separates each value from the type of evidence behind it.

Table 2. Case metrics from the author's education and production practice (compiled by the author based on the author's organizational and project records).

Element	Reported value	Evidence type
Animation school graduates	More than 25,000	Author's organizational records
Animators' Gathering festival	More than 500 participants per year	Author's event records
Festival industry partners	Autodesk, Adobe, Wacom, Playrix, Wargaming, and major studios	Partnership records
Training model	Developed and implemented with production work in Russia, Turkey, and Uzbekistan	Author's project records

The case records show the scale at which the loop operates. The school reports more than 25,000 graduates. The festival reports more than 500 participants per year and partnerships with software vendors, game-industry companies, and major studios. A training model developed with production work and implemented in three countries indicates that the loop can operate across national borders when studios supply live tasks. These figures are descriptive and cannot establish causal effects on employment or productivity. They do show that a combined education and production model can gather the studio feedback needed to update curricula, which is the mechanism shown in Figure 4.

The findings extend several lines of research. Azzarelli et al. [3] and Anantrasirichai et al. [2] review AI methods for cinematography and creative production, and their reviews largely focus on technical capability. The present study shifts attention to where these systems are placed in a production organization and who holds the decision at each point. Tang et al. [19] and Zhang et al. [20] catalog generation methods for animation and film, which supplies the technical vocabulary for the stage mapping in Table 2. Maithani [14] is the closest empirical counterpart, because it measures adoption at the level of production stages. The present study extends that measurement toward management and workforce consequences, which the stage-level benchmark does not model directly.

Work on productivity outside animation [5, 16] suggests that the time gains reported in animation case studies are plausible, but it does not establish the animation-specific effects that studios need to plan budgets and schedules. The research agendas in Amankwah-Amoah et al. [1] and Bervar et al. [4] point toward open questions about how creative work is organized around generative AI, which this article addresses. The models proposed here offer one operational response to those questions, and they are open to testing against the conditions of other studios and national labor markets.

On the basis of the synthesis, five recommendations follow. First, studios should assign a named owner to each human gate and record approvals, so that human authorship and accountability can be verified. Second, before adopting AI in a stage, studios should measure cycle time and rework rate for that stage, then measure them again after adoption using the same definitions. Third, curricula should treat prompt literacy, production constraints, and structured review as assessed skills, with feedback from studios. Fourth, studios and schools should run a pilot in which student teams work on live tasks under the gate structure in Figure 2. Fifth, style diversity should be monitored as a production metric, following the concern raised by Doshi and Hauser [8].

The sequence of the recommendations reflects dependency. Gate ownership and measurement come first, because the other recommendations require records against which to evaluate. Curriculum changes and pilot programs follow, since they depend on a clear description of the gates that students will work within. Monitoring of style diversity is placed last because it is more informative once the pipeline is stable.

Hypothesis H1 is supported in direction but not confirmed. The productivity evidence [5, 6, 16] shows gains in speed or output, and the diversity evidence [8] points to a trade-off that review can mitigate. The case records describe gate-based production, but they do not contain before-and-after measurements of cycle time or rework. The hypothesis therefore requires a controlled comparison of gated and ungated pipelines in studios.

For US clients, the models translate into procurement and contract decisions. A studio that buys AI-assisted services can ask a vendor to describe its gates, to name the reviewers, and to provide the gate record for each deliverable. Pricing can then reflect review hours, not only the time an AI tool takes to generate material. This approach supports the documentation of human authorship, which clients may need for rights and disclosure purposes, and it gives the vendor a defensible basis for estimates.

For the author's home country, the relevance lies in the link between training and production capacity. An animation workforce that can supervise AI-assisted pipelines may be better placed to serve clients than one whose work is concentrated in repetitive labor. Schools that work directly with production companies can build this supervisory capacity, and the co-production loop in Figure 4 gives a practical way to do so. The effect on national development depends on whether studios adopt the gates and whether schools keep craft training in the curriculum. The tools themselves guarantee neither outcome.

CONCLUSION

This article examined how AI changes animation production processes, production management, and professional work, and it proposed operational models for studios and schools. The first conclusion is that AI adoption is uneven across the pipeline and follows the tolerance for error at each stage. The second is that production management changes mainly in budgeting, scheduling, and quality control, and that these changes depend on where human review is placed. The third is that professional work shifts toward specification, supervision, and review, which makes training a production issue as well as an educational one. The hybrid pipeline, the task-allocation framework, and the co-production loop respond to these three conclusions. Each aim stated at the outset is addressed: production processes are mapped by stage, management effects are tied to a decision rule, and workforce and training effects are linked to a feedback loop that studios and schools can apply.

The practical significance is that studios can adopt AI with explicit gates, measure its effect on each stage, and build staffing and curricula around the review roles that AI creates. For US clients, the models offer a documented way to integrate AI while keeping human authorship visible. For the author's home country, the co-production loop shows how training and industry practice can reinforce each other. Future work should test the hypothesis through before-and-after studies in studios and should examine rights and attribution questions in more detail.

REFERENCES

1. Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management, 79*, Article 102759. https://doi.org/10.1016/j.ijinfomgt.2024.102759
2. Anantrasirichai, N., Zhang, F., & Bull, D. (2026). Advances in artificial intelligence: A review for the creative industries. *Artificial Intelligence Review, 59*(3), 1-67. https://doi.org/10.1007/s10462-026-11494-w
3. Azzarelli, A., Anantrasirichai, N., & Bull, D. (2025). Intelligent cinematography: A review of AI research for cinematographic production. *Artificial Intelligence Review, 58*(4), Article 108. https://doi.org/10.1007/s10462-024-11089-3
4. Bervar, M., Bertoncel, T., & Pejić Bach, M. (2026). Generative artificial intelligence and the creative industries: A bibliometric review and research agenda. *Systems, 14*(2), Article 138. https://doi.org/10.3390/systems14020138
5. Brynjolfsson, E., Li, D., & Raymond, L. R. (2025). Generative AI at work. *The Quarterly Journal of Economics, 140*(2), 889-942. https://doi.org/10.1093/qje/qjae044
6. Chen, Y., Wang, Y., Yu, T., & Pan, Y. (2024). The effect of AI on animation production efficiency: An empirical investigation through the network data envelopment analysis. *Electronics, 13*(24), Article 5001. https://doi.org/10.3390/electronics13245001
7. Deloitte. (2025). *TMT predictions 2025: Hollywood (and others) may be cautious about using gen AI for content creation*. Deloitte Insights. [URL to be confirmed before submission]
8. Doshi, A. R., & Hauser, O. P. (2024). Generative AI enhances individual creativity but reduces the collective diversity of novel content. *Science Advances, 10*(28), Article eadn5290. https://doi.org/10.1126/sciadv.adn5290
9. Dwivedi, Y., Kshetri, N., Hughes, L., Slade, E., Jeyaraj, A., Kar, A., Baabdullah, A., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M., Al-Busaidi, A., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642
10. Epstein, Z., Hertzmann, A., & Investigators of Human Creativity. (2023). Art and the science of generative AI. *Science, 380*(6650), 1110-1111. https://doi.org/10.1126/science.adh4451
11. Gupta, P., Ding, B., Guan, C., & Ding, D. (2024). Generative AI: A systematic review using topic modelling techniques. *Data and Information Management, 8*(2), Article 100066. https://doi.org/10.1016/j.dim.2024.100066

12. Haase, J., & Hanel, P. H. P. (2023). Artificial muses: Generative artificial intelligence chatbots have risen to human-level creativity. *Journal of Creativity, 33*(3), Article 100066. https://doi.org/10.1016/j.yjoc.2023.100066

13. Loh, N. H., Wong, N. B. R., & Jalil, M. H. (2026). Prompt literacy and generative AI readiness for AI-assisted animation creative workflows in higher education. *International Journal of Advanced Computer Science and Applications, 17*(7). [DOI to be confirmed before submission]

14. Maithani, S. (2026). Generative AI adoption in 3D animation production: A pipeline-wide empirical benchmark of early-career practitioner perceptions and the HGAI hybrid pipeline framework. *Multimedia Tools and Applications, 85*, Article 640. https://doi.org/10.1007/s11042-026-21795-5

15. McKinsey & Company. (2025). *The state of AI in 2025: Agents, innovation, and transformation*. McKinsey Global Survey. https://www.mckinsey.com/capabilities/tech-and-ai/our-insights/the-state-of-ai-2025

16. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187-192. https://doi.org/10.1126/science.adh2586

17. Orak, C. (2024). Using artificial intelligence in digital video production: A systematic review. *Journal of Educational Technology & Online Learning, 7*(3), 286-307. [DOI to be confirmed before submission]

18. Sun, P. (2024). A study of artificial intelligence in the production of film. *SHS Web of Conferences, 183*, Article 03004. https://doi.org/10.1051/shsconf/202418303004

19. Tang, Y., Guo, J., Liu, P., Wang, Z., Hua, H., Zhong, J.-X., Xiao, Y., Huang, C., Song, L., Liang, S., Song, Y., He, L., Bi, J., Feng, M., Li, X., Zhang, Z., & Xu, C. (2025). Generative AI for cel-animation: A survey. In *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops* (pp. 3837-3850).

20. Zhang, R., Yu, B., Min, J., Xin, Y., Wei, Z., Shi, J. N., Huang, M., Kong, X., Liu, N. X., Jiang, S., Bahuguna, P., Chan, M., Hora, K., Yang, L., Liang, Y., Bian, R., Liu, Y., Campillo Valencia, I., Morales Tredinick, P., . . . Rao, A. (2025). Generative AI for film creation: A survey of recent advances. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops* (pp. 6267-6279).

Copyright: © 2026 The Author(s). This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.