

Invisible Labor Behind Automation: A Study of GenAI-Assisted Animation Production in China

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Abstract

In discourse within the field of animation, generative artificial intelligence is often described as a technology that enables automation and substantially improves efficiency. This narrative strongly emphasizes AI's replacement of human labor, while overlooking the new forms of labor that practitioners contribute in this process. Taking AI-assisted production practices in China's animation industry as its research setting, this article draws on semi-structured interviews with ten animation practitioners and focuses on the new forms of labor involved in practitioners' use of Generative Artificial Intelligence. The study finds that action rhythm and narrative continuity are crucial in animation, but these requirements are misaligned with the way current generative models operate. As a result, human labor has shifted from direct manual drawing to continuous thinking, revision, and coordination. However, although these tasks constitute necessary conditions for using AI in animation production, they are often treated as part of the general process of "using AI tools" and are therefore difficult to calculate and recognize. Thus, the institutional obscuring of invisible labor involves an asymmetric structure of responsibility and power, model platforms and companies receive recognition for efficiency, while practitioners bear the responsibility for correcting deviations and ensuring delivery. By revealing these forms of invisible labor, this article calls for a re-examination of labor value, professional recognition, and the boundaries of responsibility in animation production in the AI era.

Keywords: GenAI; animation production; invisible labour; labour recognition

1. Introduction

Animation production has long been regarded as a highly labor-intensive production process. A standard-length two-dimensional animated work often requires the drawing of tens of thousands of images or even more, while in three-dimensional animation this is manifested in multiple stages, such as producing a large number of texture maps, character models, and rigs (Chen and Zwicker, 2021; Beane, 2012). Under pressures such as production cycles and labor costs, Generative Artificial Intelligence (hereinafter referred to as GenAI) has been rapidly introduced into the field of animation production (Chow and Celis Bueno, 2025).

Whether in corporate publicity, industry reports, or job descriptions, GenAI is often endowed with a nearly automated production capacity. As the platform of the Seedance model claims, "Turn a single sentence into a complete video" (Higgsfield, n.d.). According to this

imagination, GenAI seems able to quickly generate concept images, character designs, background materials, and even continuous images, thereby replacing the time-consuming drawing stages in traditional animation workflows.

However, although GenAI can provide a large number of visual results in a short period of time, it cannot automatically determine which results meet project requirements. Therefore, the process from prompt input to the final completed film is not a smooth linear one; Creators need to make sufficient preparations in the early stage, and repeatedly adjust prompts, workflows, parameters, and reference images, or screen and manually revise the generated results (Cao et al., 2026). It is precisely in this sense that GenAI should not be simply understood as replacing human labor.

The Chinese animation industry provides a representative field for examining this issue. In recent years, the Chinese animation industry has been undergoing multiple transformations of digitalization, platformization, and industrial upgrading. Many animation companies have begun to create positions related to GenAI and to introduce GenAI into multiple production stages (Anantrasirichai and Bull, 2022; SuperAGI Research, 2025). Yet enterprises have not re-established a clear mechanism for assigning responsibility, but instead treat GenAI as a new tool and hand it over to existing positions for use (Clarke and Joffe, 2025). The revision work caused by the instability of GenAI output quality is accordingly assigned to the creators' original scope of duties.

However, the narrative often attributes successful visual outputs to model capability, while failures and deviations require creators to assume responsibility for repair. This phenomenon raises questions that require further examination. Why is the newly added labor neither calculated separately nor considered worthy of additional payment? How is this asymmetrical distribution between labor and reward, responsibility and honor produced and sustained? An analysis of this process helps reveal the power relations behind the upgrading of cultural industries in the age of GenAI, and explains how so-called automated production depends on human labor that is institutionally undervalued.

2. From the Imaginary of Automation to Hidden Labor

2.1 The Automation Narrative of GenAI

Mihailova (2023) discusses the impact of GenAI on animation labour from a critical perspective, pointing out that GenAI companies often package GenAI as a tool that enables everyone to create in the name of “democratizing art”. Such statements appear to emphasize openness and participation, yet they simplify the complexity of animation into a linear process of input and output, excluding actual human labour from the narrative.

This imaginary of automation is sustained through multiple discursive fields. Commercial marketing transforms the future capacities of GenAI into promises of efficiency and market value through demonstration videos, performance comparisons, and vision statements (Borup et al., 2006; Bourne, 2024); technical evaluation systems often measure model performance through indicators such as generation speed, FID, and CLIP scores, but rarely

present how users debug models and bring out their advantages within concrete workflows (Birhane et al., 2022). In addition, media shape, mediate, and amplify public expectations of GenAI, making GenAI more easily understood as an autonomous technological subject (Brennen et al., 2022).

In the Chinese context, this imaginary of automation is also combined with the discourse of industrial upgrading. The State Council's "AI+" policy describes AI as an important force for promoting industrial transformation and cultivating new quality productive forces (State Council of the People's Republic of China, 2025); discussions related to cultural industries also regard it as an empowering tool that runs through the processes of creativity, production, and dissemination (Li, 2026). The emergence of new positions in the animation industry, such as "GenAI animation production specialist," further describes human work as the ability to master GenAI tools and optimize generated results (Chen, 2025).

Together, these tendencies produce a technological discourse in which GenAI is the protagonist and humans are placed in the background. The more the automation narrative emphasizes that models can directly generate content, the more easily the labour invested by creators to make this content usable is obscured, thereby affecting how the public, clients, and companies understand practitioners' labour.

2.2 The Medium Specificity and Requirements of Animation

Current GenAI has already been introduced into animation production workflows, and undertakes auxiliary tasks in stages such as in-between frame generation, coloring, visual effects, and storyboard production (Tang et al., 2025). However, the automation narrative equates video clips output by models with animation results that can be directly used, thereby understanding creation as a set of operations that can be replaced, and in fact overlooking the complexity of animation production.

Traditional animation production has long relied on model sheets to define character turns, expressions, key poses, and proportions, in order to maintain character consistency across different animators and shots (White, 2006). Storyboards, animatics, and layouts are used to organize shot order, eyeline direction, spatial position, and image relations, so that each shot can be connected to the progression of the preceding and following plot (Winder et al., 2020). It can thus be seen that one of the core tasks of animation production is to ensure consistency and controllability across multiple production stages.

Yet these image requirements are misaligned with the working methods of current video generation models. Video generation models usually take text prompts, images, or keyframes as conditions, and generate subsequent images according to patterns in training data. They can produce visually coherent clips within a short duration, but find it difficult to determine on their own whether the clips conform to the character designs, relations between preceding and following shots, and narrative rhythm within a project. Thomas and Johnston (1981) summarized production principles such as timing, follow-through, and squash, which are related to action rhythm, a sense of weight, and the readability of performance. Without these features, generated motion, even if visually smooth, can hardly reach the quality required by professional animation. Existing evaluations of video generation also show that

GenAI-generated videos remain unstable in the motion dimensions corresponding to these principles (Izani et al., 2025). In addition, problems such as artifacts, motion distortion, or detail errors may also occur.

Therefore, in actual production, practitioners need to compensate for these shortcomings through manual constraints and post-production corrections. For example, before generation, they may use sketches, reference images, and methods such as ControlNet to restrict the direction of generation; after generation, they may also carry out layering, lip-sync replacement, motion correction, and rhythm adjustment (Oh and Kim, 2025; Guajardo et al., 2024). In this sense, human labour remains the key to ensuring that output results can be used in production.

2.3 Invisible Labor Awaiting Recognition

In GenAI-assisted animation production, creators undertake a large amount of work, such as carrying out narrative intentions and repairing errors. These tasks all constitute the conditions that allow GenAI-assisted animation to operate, yet they are more easily underestimated.

Star and Strauss (1999) point out that not all labour that is crucial to the operation of a system can obtain the same visibility and recognition. The background work that makes formal labour possible is often excluded from formal records and evaluation systems because it does not conform to existing task classifications. For GenAI animation, what is displayed and circulated is the final image; the labour that creators invest in making GenAI-generated outputs usable is easily interpreted as a necessary process of “using tools” (Ekbja and Nardi, 2017). This mode of classification allows enterprises and GenAI systems to gain a reputation for efficiency, while practitioners’ labour of judgment and revision has greater difficulty obtaining professional recognition (Grand View Research, 2026; Kim et al., 2025).

This obscuring is also accompanied by an asymmetry of responsibility. Elish (2019) points out that, in complex automated systems, the system is often presented as intelligent and autonomous, but once problems occur, responsibility tends to fall on human operators. A similar structure also exists in GenAI animation production: the visible part of success brings technical reputation to the model, while failures and deviations are handled by creators (Porsdam Mann et al., 2023).

We argue that this silence is also related to practitioners’ own professional situation. Labour in the cultural industries has long been accompanied by instability and self-entrepreneurialization, and creators need to continuously demonstrate their ability to adapt to new technologies, bear project risks, and maintain professional competitiveness (Gill and Pratt, 2008). At the same time, redistribution in political practice often reinforces hierarchical structures, making it more difficult for the voices of those in lower positions to be heard (Swartz and Jordan, 1976).

3. Research Methods

This study adopts a qualitative research design. Taking GenAI-assisted production practices in the Chinese animation industry as its research field, it focuses on the labour that practitioners perform when using GenAI (Denzin and Lincoln, 2018).

The recruitment of interviewees followed the principle of purposive sampling, and ten people were interviewed. The positions of the interviewees cover stages directly related to animation production, such as concept design, storyboarding, and background production. The interviews were conducted through a combination of online and offline methods. Each interview lasted approximately 30 minutes. With the consent of the interviewees, the whole process was recorded and transcribed into textual materials.

Data collection adopted semi-structured interviews (DiCicco-Bloom and Crabtree, 2006). The interviews were organized around three themes: first, the actual workflows of practitioners in GenAI-assisted animation production, including in which stages GenAI is used and how the instability of GenAI outputs is handled; second, how these tasks are recorded and recognised in enterprise workflows; third, practitioners' understanding of the value of their own labour.

Data analysis adopted abductive analysis. Abductive analysis allows researchers to continuously compare findings with the theoretical framework during the analytical process. On the one hand, data are used to test the explanatory power of the framework; on the other hand, attention is also paid to unexpected findings that go beyond the expectations of the framework, and the original theory is adjusted or supplemented accordingly (Downward and Mearman, 2007).

This study follows the ethical norms of academic research. All interviewees were informed of the research purpose, the way data would be used, and the principle of anonymity before the interviews, and signed informed consent forms. Information involving companies, projects, and internal workflows was de-identified, and the names of interviewees were replaced with numbers.

4. Research Results and Discussion

4.1 The Transformation of Labor Content

Interviewees generally reported that GenAI did not reduce the total amount of labour, but changed the nature of labour. In traditional workflows, work usually appears as relatively clearly defined job tasks. In GenAI-assisted workflows, however, it gradually expands into judgmental and transformative work organized around GenAI-generated materials. These tasks likewise consume time and professional judgment, yet they are included in the general process of “using GenAI tools,” making them more difficult to identify and calculate separately than traditional drawing labour.

First, a large amount of preparatory labour already exists before GenAI generation. Creators need to understand project requirements, organize scripts, storyboards, reference images, character settings, and stylistic directions, and then transform these contents into inputs that the model can process. Multiple interviewees believed that the premise for GenAI to generate

qualified images is that creators have already completed a large amount of judgment concerning direction and standards.

Second, GenAI-generated materials usually need to undergo manual processing before they can be used in subsequent production. In the interviews, “drawing cards,” “debugging,” and “revision” were frequently mentioned descriptions of work. Some interviewees also pointed out that GenAI video tools have limited duration for each generation, and that when multiple clips are stitched together, color jumps and image scaling often occur. In a project cycle of four weeks, one week may be spent aligning the breakpoints between clips. Similar situations also exist in the direction of three-dimensional models. After GenAI generates a model, manual refinement, cutting, and polygon reduction are still required. It can thus be seen that taming the instability of GenAI is becoming a new type of labour.

This transformation of labour content has also brought an increase in cognitive burden. GenAI saves part of the time spent on manual drawing or modelling from scratch, but increases the frequency of judgment and checking. P1 mentioned that after using GenAI, the volume of demand became about four times what it had been before; work shifted from execution to judgment, and mental consumption increased significantly. P5 also pointed out that the GenAI generation process interrupts continuous thinking, and practitioners need to repeatedly switch between waiting for generation, handling other tasks, reviewing results, and making revisions again.

Overall, GenAI redistributes the types and intensity of animation labour. The apparent improvement in efficiency conceals the shift in labour forms.

4.2 Conditional Efficiency

The interview materials show that practitioners’ evaluations of GenAI efficiency are clearly divided. Some practitioners believe that GenAI has indeed improved efficiency, while others believe that GenAI has increased their workload. We understand this as meaning that the efficiency of GenAI is formed within specific production conditions. It depends on what tasks GenAI is used for, which stage of production it is in, how high the project’s quality requirements are, and whether the company provides sufficient tool resources and time support.

When GenAI is used for early-stage reference or communication demonstrations, it is more easily perceived as a tool for improving efficiency. In storyboard work, P8 mainly uses GenAI for early-stage communication, in order to more intuitively show the general effect of scenes such as chase sequences; P7 usually first draws a complete sketch, and then lets GenAI supplement materials, colours, and visual effects. In these scenarios, the images generated by GenAI only need to have a clear structure, and creators basically do not need to revise them, thus reducing a great deal of production time.

However, when high-precision visual results need to be produced, the efficiency of GenAI becomes less stable. P5 proposed that GenAI generation has difficulty advancing according to the original storyboard design, which may increase rework because it cannot meet the requirements. Another interviewee also mentioned that storyboards generated by GenAI have “almost no audiovisual language, and can only serve as a source of inspiration.”

In addition, the efficiency of GenAI is also affected by quotas, accounts, queuing time, and the company's allocation of resources. P3's company provides additional accounts, so there is less pressure from generation quotas; P8 mentioned that the GenAI expenses available to each person in a project are limited, and if suitable results cannot be generated within the prescribed quota, the remaining costs may be paid by employees themselves. Some participants also discussed the experiences of friends, pointing out that platform queuing and quota reset mechanisms change the arrangement of working time, and some companies even begin work in the early morning to avoid peak generation periods.

This finding also revises this article's understanding of the automation narrative. The automation narrative is not necessarily entirely false; rather, it universalizes the partial efficiency that holds under specific conditions, and extends this partial efficiency into a judgment about the entire production workflow. Leonardi (2011) points out that the actual effects of technology depend on how technology is combined with work routines; studies of technological affordances also emphasize that the effects of technology cannot be understood apart from specific contexts of use (Faraj and Azad, 2012). Invisible labour does not appear equally in all GenAI use scenarios, but is increased when enterprises arrange production cycles, outputs, and evaluation on the premise that "GenAI has already improved efficiency," while not simultaneously calculating the cost of human transformation.

4.3 Asymmetry of Responsibility

In traditional animation production, the relationship between power and responsibility is relatively clear. For example, key animators control their own brushwork and images, and background artists control their own colours and compositions. They are both the executors of labour and the determinants of quality. In GenAI-assisted workflows, however, although creators are still required to be responsible for the results, the scope they are able to control has been greatly reduced.

First, the technical system itself contains uncontrollable variables. The generation quality of GenAI models is constrained by external factors such as the distribution of training data, model version updates, platform service stability, and even token quotas. P6 mentioned that the same set of prompts may generate very different results at different times, and that after a model update, parameters that were originally usable may also become invalid. Creators cannot fully explain why generation quality fluctuates, and can only screen usable results through repeated attempts.

Second, project standards and evaluation standards are likewise beyond creators' control. Client requirements, superiors' judgments, and adjustments to project style determine what counts as a qualified image, while GenAI has difficulty automatically adapting to these changes. P2 pointed out that superiors may not be clear about what they want, yet still require creators to continuously use GenAI to produce options for selection. The rapid generation capacity of GenAI may instead expand the number of options and rounds of revision, allowing vague requirements to be transferred to creators more quickly.

Faced with this pressure of responsibility, practitioners usually maintain efficiency and psychological balance through individualised methods. Some actively learn to build their own

workflows and manually record effective parameters in order to reduce the probability of generation failure; others distinguish between the use of GenAI in company projects and in personal creation, treating GenAI as a tool for completing tasks at work, while preserving confirmation of authorship and the value of skill in personal creation. However, some interviewees and their friends or relatives have considered, or have already chosen, leaving the animation industry because of GenAI-related work pressure. These responses show that practitioners are not unaware of the existence of additional labour, but often understand it as a matter of personal ability or project adaptability. Precisely because of this, invisible labour in GenAI production is more easily dealt with in individualised ways, and is difficult to transform into formal negotiation at the level of responsibility and remuneration.

The moral crumple zone theory of Elish (2019) mentioned in Section 2.3 reveals how responsibility is gathered from system conditions onto individual creators. However, why do practitioners not only bear this distribution of responsibility, but even actively make self-adjustments and exercise self-restraint? The theory of responsabilization provides a supplementary explanation: in the GenAI production environment, enterprises and platforms do not need to directly manage every specific operation, but instead make creators take on the responsibility of adapting to technology themselves through efficiency requirements, expectations of tool use, and evaluation of final results (Hysing, 2021).

5. Conclusion

Based on semi-structured interviews with Chinese animation practitioners, this article examines the concrete practices of GenAI-assisted production in the Chinese animation industry. The study argues that the role of GenAI in animation production is that of an auxiliary tool that requires continuous human supervision and transformation. There is a fundamental misalignment between the animation medium's requirements for expressiveness and narrative, and the current logic of GenAI generation. Therefore, the repair labour and cognitive labour invested by practitioners are indispensable to the human-machine collaborative mode of production.

The lag of the current institutional framework is not only a problem of the animation industry, but also a common challenge faced by the entire creative industry in the age of GenAI. For institutional design, the key lies in how to make human labour visible. Only by recognizing the invisible labour that maintains the operation of automation can industrial narratives about GenAI shift from the self-display of technology to the respect that labouring subjects deserve.

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