

A Systematic Review of Generative AI on Game Character Creation: Applications, Challenges, and Future Trends

Zhenhua Wu^{ID}, Zhuohao Chen, Di Zhu, Christos Mousas^{ID}, *Member, IEEE*, and Dominic Kao^{ID}

Abstract—In this article, we review the impact of generative artificial intelligence (AI) on game character creation. We critically examine the application of AI-driven computer graphics (AICG) technology across the character creation workflow, including concept generation, clothing design, modeling, props, cultural embedding, personality traits, and behaviors. Our research identifies potential applications, challenges, and future trends of these technologies in game development. Furthermore, it explores how AI and large language models can streamline workflows, automate asset generation, and reduce technical barriers in character creation. In this systematic review, we provide valuable insights for AI developers, game designers, and researchers.

Index Terms—Game character creation, generative artificial intelligence (GenAI), human–artificial intelligence (AI) interaction, large language models (LLMs).

I. INTRODUCTION

ARTIFICIAL intelligence (AI) and large language models (LLMs) are fundamentally reshaping industries from top to bottom. Initially, AI was mainly used to automate repetitive tasks, such as text generation, information retrieval, summarization, and generalization [3]. However, the advent of generative artificial intelligence (GenAI) has introduced creative capabilities, enabling the generation of images, models, and animations [2], [3]. This technology might improve designers' and developers' creativity and productivity, signaling the onset of the next technological revolution [1].

Game development is one of the sectors most impacted by GenAI [3]. Key transformative applications include the creation of virtual characters and the automatic generation of game assets [1]. As games become increasingly complex and personalized, the design of realistic, culturally relevant, and emotionally resonant characters has become critical [2]. This process presents significant challenges for character designers, who must excel in 3-D modeling and understand the implicit

reasoning behind a character's appearance, including its cultural and behavioral context. Addressing these challenges necessitates innovative tools and techniques beyond traditional design methods.

In the exploratory stage of game character creation, designers can leverage LLMs, such as GPT-4o,¹ to develop detailed character backgrounds. These models can provide insight into the character's history, culture, and nationality while ensuring alignment with the narrative of the game [1], [3], [4]. During the visual design stage, GenAI can generate realistic pictures, models, and 3-D animations based on the designer's descriptions and LLM-provided details. The integration of LLMs and GenAI enhances visual and behavioral realism while enabling more efficient and accessible content production [1].

Another significant challenge for game designers and developers is the systematic refinement of prototypes during iterative character development [4]. This process involves implementing, testing, and often discarding numerous design inspirations, which is time-consuming and places considerable pressure on designers to meet deadlines. GenAI can assist by precisely adjusting specific design elements, automating the creation of new game assets, and modifying existing ones. It can then also support the subsequent stage of fine-tuning character parameters and testing behaviors [5] using requirement descriptions. This technology can reduce the technical burden on designers and reduce development overhead.

This review aims to critically examine the use of GenAI and LLMs in virtual character design using traditional industry workflow as a reference. We focus on each stage involved in industry practice, emphasizing key elements of the character art design workflow [73], [74], [75], [76], [77]. By categorizing these elements and analyzing how GenAI and LLM technologies contribute to these processes (see Fig. 1), we address the following research questions.

- 1) *RQ1*: How can GenAI and LLMs streamline workflows in game character design?
- 2) *RQ2*: How do current GenAI and LLM tools function, and what are the core technologies?
- 3) *RQ3*: What are the current challenges and future trends in applying these technologies?

The remainder of this article is organized as follows. Section II introduces background and related work on GenAI and LLMs in game development. Section III outlines the methodology for the systematic literature review. Section IV presents statistics of the search results. Section V explores the role of GenAI and LLMs

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¹GPT-4o: <https://openai.com/>

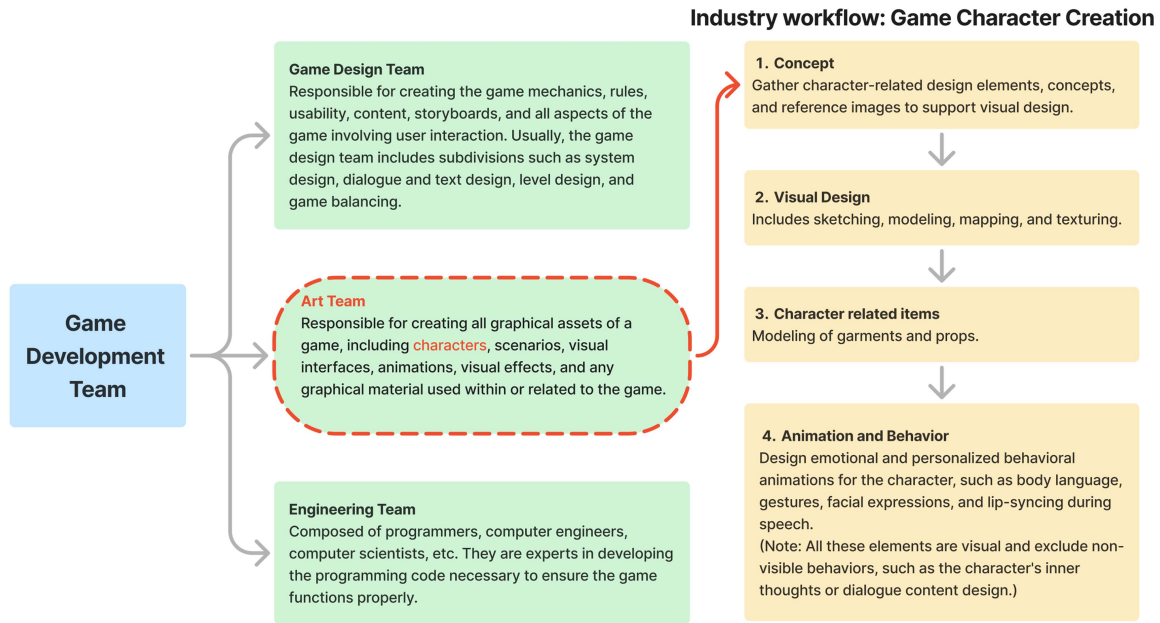


Fig. 1. Research topics, traditional industry descriptions, and game character design workflow [73], [74], [75], [76], [77].

at each stage of character creation. Section VI discusses the findings, future directions, implications, and recommendations. Section VII highlights the limitations of the study. Finally, Section VIII concludes the article.

II. BACKGROUND AND RELATED WORK

A. GenAI and LLMs in the Development of Games, Characters, and Narratives

GenAI and LLMs have reshaped workflows and unlocked creative possibilities in game development [1]. Using tools, such as DALL-E,² Stable Diffusion,³ and Meshy AI,⁴ designers can generate high-quality assets, including character visuals, props, and environments, with unprecedented speed and efficiency [1], [3]. These technologies simplify the iterative process, enabling rapid prototyping and reducing resource constraints, especially for small studios and independent developers [72].

GenAI and LLMs also play a significant role in game character design by automating labor-intensive tasks and enhancing creative exploration. Tools, such as text-to-image generators accelerate the creation of visual assets, such as characters, costumes, and props, while 3-D modeling systems, such as 3-D Gaussian Splatting⁵ and ASH⁶ [30] streamline animation workflows [1]. These innovations enable an iterative design process, allowing designers to test and refine prototypes quickly while fostering closer collaboration between creative designers and technical developers by breaking down traditionally siloed roles [4].

In addition, GenAI and LLMs have improved narrative design by generating rich backstories and dynamic dialogue for game characters. These models improve NPC (Non-player character)

responses, making them more personalized and realistic by creating emotionally engaging, context-aware narratives [2]. For example, tools, such as GPT-4 have been used to generate dialogue that adapts to player input, enhancing immersion and gameplay experience [69]. Moreover, recent studies also highlight the importance of audio and dialogue customization in enhancing player experience.

B. Challenges of GenAI and LLM Integration in Game Development Workflows

Integrating GenAI and LLMs into game character design workflows faces many technical, creative, and ethical obstacles. Traditional character design workflows are iterative, moving from low-fidelity sketches to high-fidelity models; while GenAI accelerates prototyping, seamless integration of all phases remains challenging. Zhu and Wang [4] note that model-driven game development (MDGD) simplifies prototyping but requires additional effort to align AI-generated assets with domain-specific requirements. Similarly, Sweetser [2] highlighted the difficulty of integrating LLM-generated narratives and dialogues with character visuals and behaviors, often requiring significant human intervention.

Mid-fidelity prototyping is crucial for harmonizing visual and narrative elements but has not been fully explored in terms of AI support. Maintaining stylistic consistency in AI-generated assets is another issue. As Hu et al. [1] noted, tools, such as DALL-E, need to be manually fine-tuned to match predefined art styles. In games with interconnected storylines, inconsistencies in character aesthetics or behaviors can break player immersion and need to be corrected by designers [3].

Usability issues also hamper cross-disciplinary collaboration. For example, Zhu and Wang [4] highlighted the need for domain-specific modeling to improve communication between designers and developers. However, balancing technical complexity and accessibility remains challenging, especially for nontechnical designers [69]. Real-time customization and character behavior testing are also limited because GenAI tools

²DALL-E: <https://openai.com/index/dall-e-3/>

³Stable Diffusion: <https://stablediffusionweb.com/>

⁴Meshy AI: <https://www.meshy.ai/>

⁵3-D Gaussian Splatting: <https://repo-sam.inria.fr/fungraph/3d-gaussian-splatting/>

⁶ASH (Anything Similar Hypernetwork): <https://vc.ai.mpi-inf.mpg.de/projects/ash/>

are not optimized for iterative adjustments based on team or user feedback [1], [72].

Finally, ethical issues, such as cultural sensitivity in character design and biases in generative outputs, require greater attention. Jiang et al. [70] warned that AI training datasets might perpetuate stereotypes or lack cultural nuance, necessitating additional scrutiny and intervention from designers.

C. Opportunities and Future Directions

GenAI offers significant opportunities to democratize game character design by lowering technical barriers and facilitating cross-disciplinary collaboration. These tools allow small studios and independent developers to prototype and iterate on ideas more efficiently, fostering innovation across the industry [3], [72]. Additionally, AI-driven systems are anticipated to enhance workflow efficiency, enabling faster testing and refinement while maintaining quality [1].

D. Research Gaps

In this article, we address existing research gaps by presenting representative approaches to the application of GenAI and LLM tools throughout the complete game character design workflow, including content generation, core technologies, tuneability, and workflow facilitation.

- 1) In terms of end-to-end workflow integration, most research focuses only on isolated applications of GenAI, such as rapid prototyping or dialogue generation, and rarely explores the complete character design process, from ideation and conceptualization to final testing and deployment [4], [69]. For example, the iterative nature of medium- to high-fidelity prototyping and behavioral modeling remains understudied, and designers lack frameworks or tools that can simultaneously refine character aesthetics, narrative, and behavior, resulting in a significant need for manual manipulation [2].
- 2) In terms of cultural and behavioral modeling, research has yet to adequately address how GenAI can support culturally curated and behaviorally realistic character design. While GenAI and LLMs can aid in the creation of backstory and dialogue, its limitations in capturing cultural and behavioral depth limit its utility in character creation that resonates with diverse audiences [70].
- 3) In addition, current tools often suffer from hegemonic cultural biases in the training data, and further research is needed to mitigate these biases [3], [70].
- 4) In terms of practical evaluations and case studies, Zhu et al. [4] emphasized the importance of empirical validation for evaluating MDGD methods, but similar practical evaluations are lacking for GenAI applications in game character design, with few case studies demonstrating the performance of AI tools in realistic scenarios [69].
- 5) In terms of technical and usability barriers, textual input limitations make it difficult for tools like DALL-E to interpret abstract or unconventional creative inputs, resulting in outputs that may not meet designers' expectations [3], [72].
- 6) In terms of interdisciplinary collaboration, Zhu and Wang [4] emphasized the importance of interdisciplinary workflows. However, research exploring how GenAI can facilitate collaboration between designers, developers, and narrative writers remains limited. There is a significant

need for tools that effectively bridge technical and creative domains to fully leverage the potential of AI in game development.

III. METHODOLOGY

We conducted a systematic literature review using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines to delve deeper into our research questions.

A. Search Strategy

We created a search string to screen literature that would assist in answering these research questions. Based on the workflow of game character design and the components of game characters, we categorized and finally set the search string as a short string consisting of an AI-related term combined with a specific design domain keyword group. This allows us to roughly categorize the papers during the first screening and prepare for a more refined search in the second screening.

The AI-related terms in the search string were: ("LLMs" OR "LLM" OR "AI" OR "DALL-E" OR "ChatGPT") AND ("Character"). Moreover, the design domain-specific keywords included in the search string were: ("character design" OR "game character" OR "game design" OR "character animation" OR "character model" OR "NPC" OR "avatar" OR "design ethnography" OR "character behavior" OR "character personality" OR "cultural relevance").

B. Database and Search Limitations

For this literature review, we used five digital library databases as information sources: the Association for Computing Machinery (ACM Digital Library), the Institute of Electrical and Electronics Engineers (IEEE Xplore), SpringerLink, ScienceDirect, and Scopus. These databases are widely recognized for their extensive collections of peer-reviewed publications and emphasis on academic rigor. Although we also reviewed other databases, such as Web of Science, JSTOR, Wiley, and Taylor and Francis, the literature found in these databases was very limited, and the few articles available all overlapped with the content from the five primary databases we used.

To ensure the relevance of our findings, we applied a key limitation regarding publication dates. During the literature search, we focused on studies published within the last five years, reflecting the rapid advancements in AI. While earlier works provide foundational insights, this review aims to capture the most recent developments in AI and video game character design, best represented by recent publications. As a result, we excluded from the analysis any papers published before 2019. Direct screening through the advanced search function of the digital library initially identified 6120 potentially relevant studies as of 10 October 2024.

C. Study Selection Process

The final study selection process was rigorous and carefully designed to minimize bias in the final results.

1) Inclusion Criteria:

- a) Studies describing technology or content relevant to video game character art design, especially papers focused on material related to visual effects and graphics.

- b) Studies primarily discussing the application and testing aspects of AI tools.
- c) The content of the studies should include the workflow of the AI application being introduced, multiple output examples, and relevant data, such as accuracy and generation time.
- d) The AI applications in the studies should be easy to implement, with reasonable hardware requirements (e.g., running the AI model should only require a workstation equipped with a high-performance graphics card rather than a large server with multiple graphics cards).

2) Exclusion Criteria:

- a) Research not directly related to relevant AI applications or video game character art design, such as studies primarily focused on characters' inner thoughts or dialogue content design.
- b) Research that is not directly related to the application of AI tools but rather focuses on fundamental technical issues, such as algorithms and training of AI models.
- c) Studies with incomplete content, for instance, those lacking a clearly defined workflow or presenting ambiguous data.
- d) Research involving AI implementations that are impractical or excessively demanding in terms of hardware, such as requiring extensive server infrastructure or multiple high-performance cameras (e.g., for neural radiance fields).

3) Literature Screening:

- a) *Preliminary screening:* Conducted independently by two researchers. During the review process, the focus was on reviewing the paper's title, abstract, and flowcharts of AI applications, along with generated visuals, to determine if they align with the research objectives. The papers are roughly categorized based on the steps of the game character design workflow.
- b) *Second screening:* Three researchers conducted a full-text review. They checked whether the content of the collected papers was complete and met the paper selection criteria we had set. Only articles directly involving one or more steps in character design were considered for citation.
- c) *Third and final screening:* Three researchers were involved in a more detailed review of the selected articles. The focus at this stage was on examining the specific content of the papers, such as the validity of the testing methods, data, and conclusions. Papers with similar functions were compared, and more comprehensive AI features and test results were selected.

4) *Final Selection:* Following this literature screening, we selected 72 studies for inclusion in the systematic review. Each study met all the inclusion criteria and did not meet any exclusion criteria. See Fig. 2, 3, and 4.

IV. RESULTS

In this section, we compiled the systematic review results according to the restricted research objectives. We included 72 papers. Of these, 48.6% were published in scientific journals, and 51.3% were published as conference papers. In terms of publication, 52 papers originated from the ACM Digital Library (72.2%), followed by IEEE Xplore with 19 papers (26.3%), and finally, SpringerLink with two papers (2.7%).

In terms of the research content of the examined papers, there are seven (9.7%) review papers and surveys, 60 (83.3%) AI

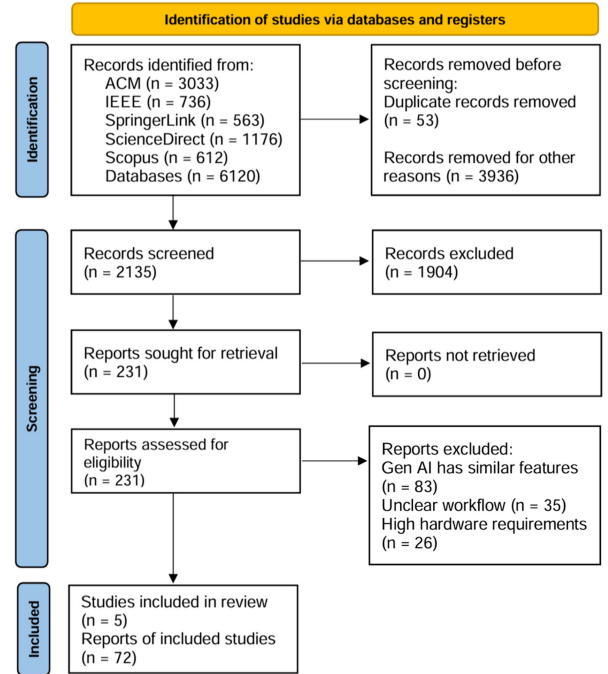


Fig. 2. Literature identification and screening process flow chart is based on the PRISMA guidelines.

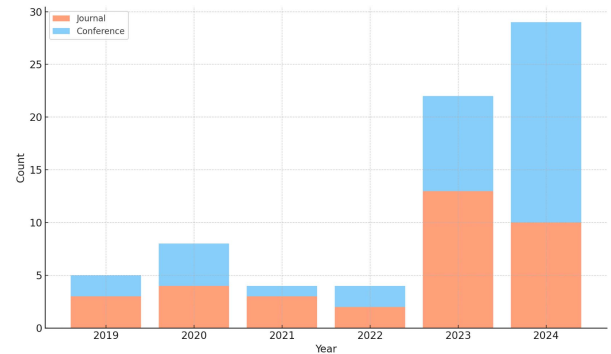


Fig. 3. Numbers and types of papers cited per year.

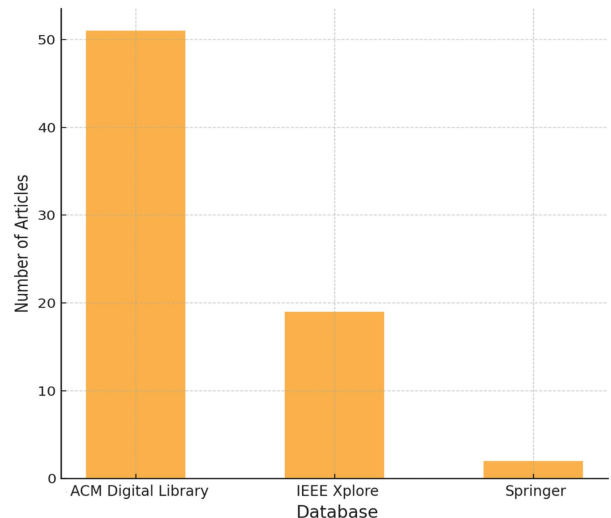


Fig. 4. Numbers and types of papers cited from each database.

TABLE I
WORKFLOW AND SEGMENT WORKFLOW WITH COUNTS AND REFERENCES

Workflow	Segment Workflow	Count	Citation
1. Conceptualization	• LLMs Support Game Character Conceptualization	5	[5]–[7], [9]
2. Character Visual Design	• Mid-Fidelity Character Head Sketching • High-Fidelity 3D Head Modeling • Adding Details to Character Heads • Character Face Model Editing • Generating 2D Character Body Designs • Generating Mid-Fidelity 3D Body Models • Adjusting 3D Character Body Postures with GenAI and LLMs • Optimizing 3D Character Body Joints Using GenAI	2 4 2 4 3 3 3 2	[10], [11] [12]–[15] [16], [17] [18]–[21] [22]–[24] [27]–[29] [30]–[32] [25], [26]
3. Character Props and Garment Design	• Generating Stylized Garment Images for Characters • Generating 3D Clothing on Character Bodies • Independent 3D Clothing Model Generation • Generating Character Prop Sketches • Generating 3D Props for Characters • Generating Stylized 3D Prop Textures • Generating Prop Interactions and Animations	1 3 2 1 3 2 1	[33] [34]–[36] [37], [38] [39] [40]–[42] [43], [44] [45]
4. Character Behavior and Animation	• Generating 2D Animations from Sketches • Generating Detailed 3D Head Animations for Characters • Generating Character Lip Shapes and Facial Expressions • Generating Gestures and Behaviors for Game Characters • Generating Simple Character Actions • Generating Complex and Specialized Stylized Actions • Animating Character Facial Expressions and Body Movements • Generating Stylized Character Voices • Generating Stylized Dance Animations	1 2 3 4 3 3 1 1 2	[46] [47], [48] [53]–[55] [56], [57], [58], [59] [60], [61], [62] [63], [64], [65] [49] [50] [51], [52]

TABLE II
INPUT AND OUTPUT MAPPING WITH COUNTS AND REFERENCES

Input	Output	Count	Citation
Text	3D Model	6	[15], [17], [28], [36], [42], [45]
Text	Animation	7	[24], [45], [48], [49], [60], [61], [62]
Text	Image	6	[5], [22], [23], [24], [33], [39]
Text	Script	1	[6]
Text	Story and Personality	3	[7], [9]
Image	3D Model	13	[12], [13], [14], [16], [18], [19], [20], [27], [34], [35], [37], [38], [42]
Image	Animation	1	[46]
Image	Image	2	[10], [18]
Sketch	3D Model	3	[11], [40], [42]
Picture	Voice	1	[50]
Audio	Animation	8	[51], [52], [53], [54], [55], [57], [58], [59]
Video	3D Model	4	[29], [30], [31], [37]
Video	Animation	4	[15], [56], [62], [63], [65]
3D Model	3D Model	5	[21], [26], [41], [43], [44]
3D Model	Animation	1	[25]
3D Model	Image	1	[32]
Action-tracking	Animation	1	[64]

research and application papers, and five (6.9%) research papers on risk, policy, and impacts from AI.

AI research and application-type papers are the main research part of this article and are used to answer most of the research questions. By referring to Canheti et al. [76] and Mi et al.’s [77] studies on the game character design process, we decided to categorize the articles according to two different perspectives: the application of segment workflow corresponding to different AI frameworks (see Table I) and the input and output methods of AI frameworks (see Table II). In the Supplementary Materials, we provide more details about the features, performance data, AI core technology, and advantages and disadvantages.

V. FINDINGS

A. Conceptualization

1) *How GenAI and LLMs Support Character Conceptualization (RQ1)*: During the conceptualization phase, LLMs, such as GPT-3.5 and GPT-4, have emerged as powerful tools for streamlining game design workflows. These models translate textual prompts into a wide range of creative suggestions, including character traits, abilities, and thematic inspirations, which are

used to assist in the visual and behavioral design of the character, significantly improving development efficiency. For instance, the “Ink Splotch Effect” case study illustrates how LLMs act as high-level creative collaborators, generating innovative features, such as teleportation or gravity manipulation, that directly influence character visualization and interaction [6]. This capability empowers designers to experiment with novel ideas, reducing creative barriers and broadening conceptual exploration.

Moreover, LLMs integrate seamlessly with frameworks like Sketchar⁷ to generate basic character backstories and interpersonal relationships through text input. These concepts are further refined by generative tools, such as DALL-E, to produce visual prototypes (see Fig. 5) [5]. This iterative process enables nonprofessional illustrators to create initial character designs efficiently, promoting interdisciplinary collaboration. In addition, retrieval-augmented generation (RAG) enables GenAI to dynamically align a character’s backstory and behavior with a game-specific knowledge base [7]. By embedding the output into a narrative framework, LLMs ensure thematic coherence and narrative consistency.

⁷Sketchar: <https://sketchar.io/>

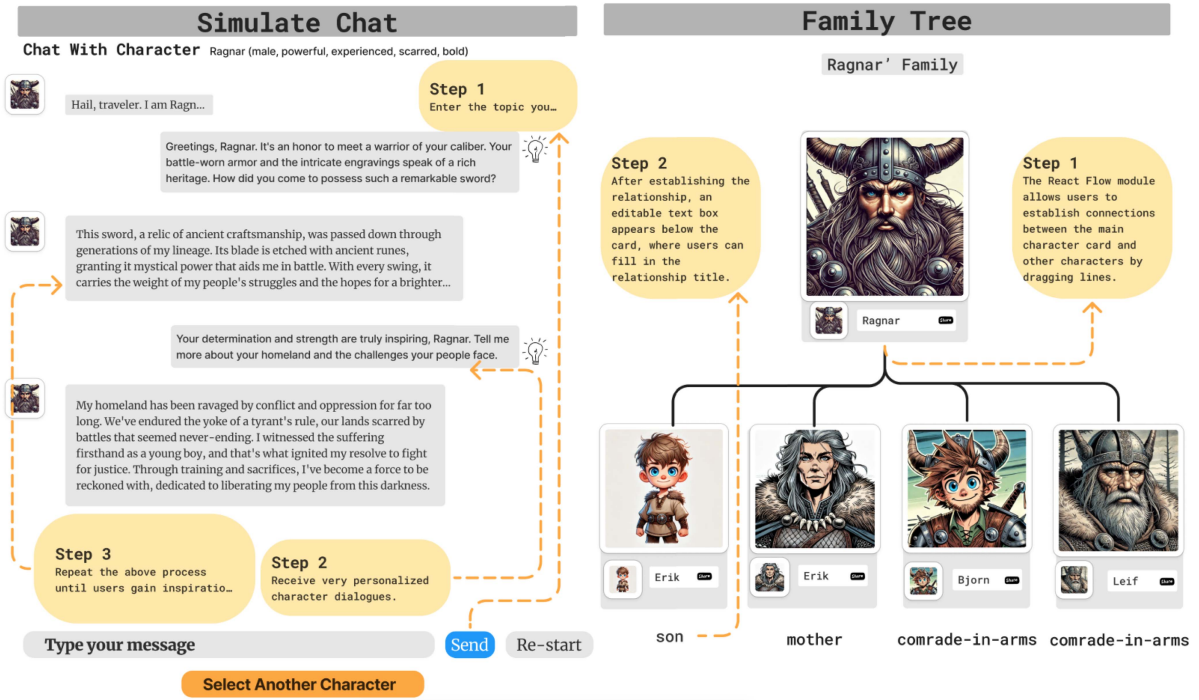


Fig. 5. “Simulate Chat Workflow: Step 1, Enter the chat contents. Step 2, Receive a personalized answer. Step 3, Repeat the process. Family Tree Workflow: Step 1, Utilize the ability of React Flow Module to build relationships by dragging lines. Step 2, Fill in the relationship name below the card.” (Figure reproduced with permission from [5], caption quoted verbatim).

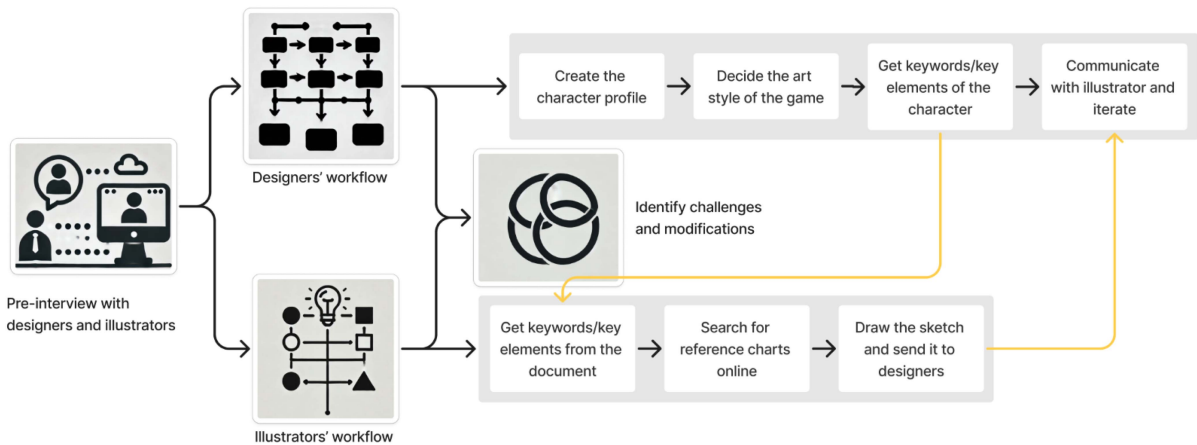


Fig. 6. Collaborative pathway and workflow of designers and illustrators (Figure reproduced with permission from [5]).

A key strength of LLMs in conceptualization is their ability to enhance personalization and creativity by generating diverse, culturally adapted personas that enable designers to explore innovative inspirations [9]. By streamlining the prototyping process, facilitating rapid iteration, and minimizing repetitive tasks, they can enhance workflow efficiency. In addition, LLMs deepen cultural relevance and emotional variation for character design, enhancing realism by reconciling character behavior with narrative context [9]. Integrating LLMs with tools like Sketchchar facilitates cross-disciplinary collaboration, enabling seamless communication between designers and illustrators (see Fig. 6) [5].

2) *Current Limitations of GenAI and LLMs Supporting Character Conceptualization (RQ3):* Limitations of LLMs for character conceptualization include a high requirement for precision

in the content of textual cues and possibly special structural requirements, which may limit creative flexibility [9]. A misunderstanding of the prompts may cause the output to deviate from the intended design goal or lack personality [6]. In addition, cultural biases in the training data can lead to outputs that are not inclusive or representative of different audiences [9]. Configuring multidimensional metrics for fine-grained behavioral modeling still requires significant work and is ambiguous [9]. Finally, inconsistencies in knowledge modeling may produce incoherent responses, especially if contextual consistency is not strictly maintained [7].

3) *Core AI Technologies and Overall Trends in GenAI and LLMs Supporting Character Conceptualization (RQ2):* Combining LLMs with generative frameworks, such as DALL-E and RAG, has become a defining trend in character

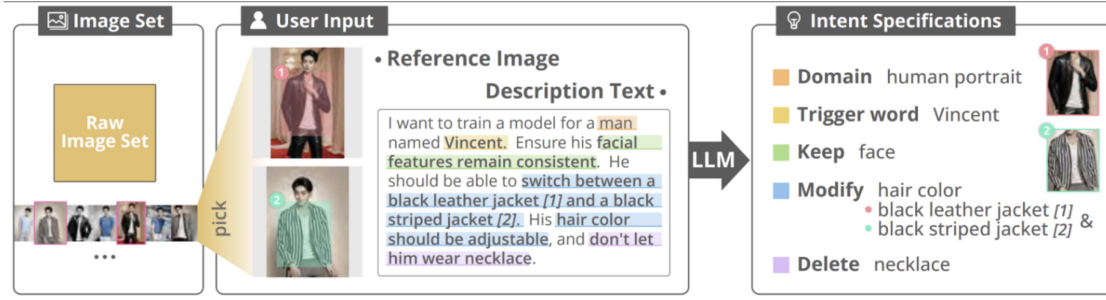


Fig. 7. “Language-vision intent input and transformation. We allow users to provide detailed multi-modal input to clarify their intents, including the description text and reference images. Powered by the language model, the user input will be transformed into intent specifications, including trigger words, domain, concepts, and operations.” (Figure reproduced with permission from [23], caption quoted verbatim).

conceptualization, enabling the transformation of theoretical concepts into visual prototypes and embedding cultural and behavioral subtleties into the design focus, coinciding with the growing demand for immersive, player-centered experiences [5], [7]. Transformer-based frameworks, such as GPT-3.5 and GPT-4, offer robust capabilities for natural language understanding and generation. RAG further enhances these models by combining outputs with domain-specific knowledge, ensuring consistency and relevance [7]. In addition, tools like Sketchar bridge the textual and graphic design domains by integrating the functionality of LLMs with visual GenAI using an application programming interface (API) [5]. We provide detailed data in the Supplementary Material.

B. Character Visual Design

1) *How GenAI and LLMs Support the Creation of Character Visuals (RQ1)*: With the assistance of GenAI, complex design work can be automated. For example, tools, such as EmoG, simplify early prototyping by converting neutral sketches into expressive character visuals, saving time and effort [10]. Similarly, SketchMetaFace enables a rapid transition from 2-D sketches to detailed 3-D deep models, significantly accelerating mid-fidelity modeling [11] (see Fig. 8).

Tools driven by GenAI can also bridge the gap between concepts and visual prototypes. For example, DreamFace [15] and the frameworks of Bao et al. [12] leveraged advanced 3-D deformable models to generate realistic head models, allowing customization through intuitive inputs, such as textual prompts or simple images [13]. This capability accelerates high-fidelity prototyping while providing precise control over visual features. Text2AC [24] can automatically create full-body graphics of characters with dynamic skeletons for integration with game engines, such as Unity.

In terms of improving design efficiency, reducing technical barriers, and democratizing the creative process, frameworks such as DreamFace [15] and CharacterGen [27] integrate multimodal input, allowing the creation of realistic avatars that are both visually appealing and culturally resonant. The significant advantage of Promptify [22] and IntentTuner [23] (see Fig. 7) is the ability to edit design elements visually. Designers can adjust individual design elements of generated content through text interaction, making the generated content highly stylized and enabling mass-production of images that conform to these design elements. In addition, frameworks, such as SMPL-1K [26] (see Fig. 9) and Ash [30] (see Fig. 10), can simplify complex processes such as body joint modeling and pose generation,

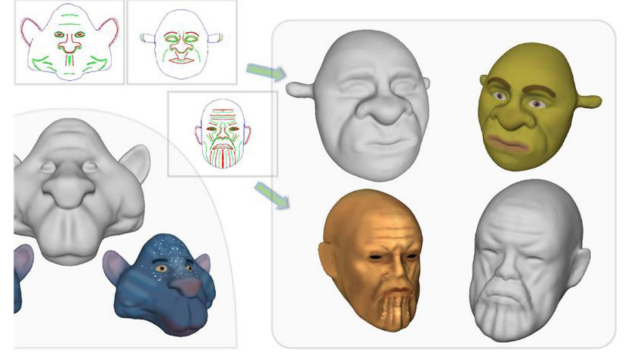


Fig. 8. “We present SketchMetaFace, a novel sketching system designed for amateur users to create high-fidelity 3D character faces. With curvature-aware strokes (valley strokes in green and ridge strokes in red), novice users can smoothly customize detailed 3D heads. Note that our system only outputs geometry without texture and texturing is achieved using commercial modeling tools.” (Figure reproduced with permission from [11], caption quoted verbatim).

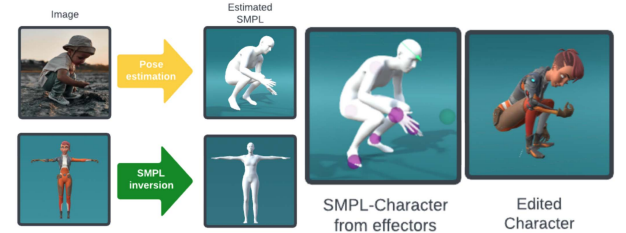


Fig. 9. “Pipeline for pose estimation and editing from a 2D image on a custom humanoid character.” (Figure reproduced with permission from [26], caption quoted verbatim).

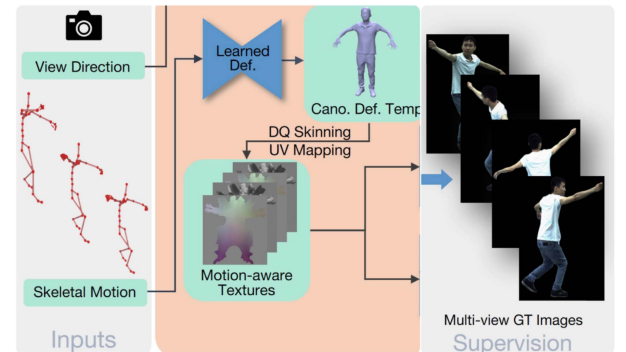


Fig. 10. “ASH generates high-fidelity rendering given a skeletal motion and a virtual camera view.” (Figure reproduced with permission from [30], caption quoted verbatim).



Fig. 11. Given a text description, this model can produce realistic human hairstyles (Figure reproduced with permission [17]).

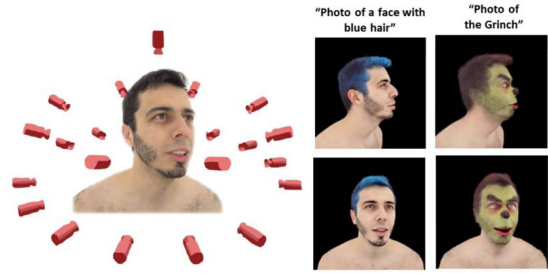


Fig. 12. This AI framework can produce “pleasing text-driven visual edits for different prompts” (Figure reproduced with permission from [19]).

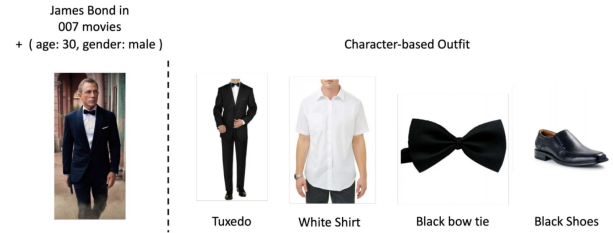


Fig. 13. “Generated outfit (right panel) based on James Bond character (left panel).” (Figure reproduced with permission from [33]).

ensuring cross-platform compatibility and enhancing rapid prototyping workflows.

2) *Current Limitations of GenAI and LLMs Supporting the Creation of Character Visuals (RQ3)*: Despite their transformative potential, AI-driven game character design tools face several limitations. For example, SketchMetaFace (see Fig. 8) struggles with complex depth variations and relies on a frontal viewpoint, limiting modeling versatility [11]. CharacterGen requires high-performance hardware and long rendering times, which presents an accessibility barrier for smaller studios [28]. High-resolution systems (e.g., DSLR-based photogrammetry) require expensive equipment and precise setups, which can be cost-prohibitive for small studios and independent developers [13]. The AI frameworks of CharacterGen [27] and Wenninger et al. [29] can cause the generated content to be noisy due to illumination or occlusion problems of the input content and require further optimization. In addition, EmoG relies on the quality and diversity of the training dataset, which can lead to homogenization of generated content [10]. Addressing these challenges requires more diverse and inclusive training datasets, increased adaptability of AI frameworks to nonroutine inputs, increased computational efficiency, and better integration of human creativity into automated workflows.

3) *Core AI Technologies and Overall Trends in GenAI and LLMs Supporting the Creation of Character Visuals (RQ2)*: Common core technologies of these AI tools are convolutional neural networks (CNN) [10], [25], variational autoencoders [17], [21], and pixel-aligned implicit functions [10], [11] to improve geometric and texture fidelity. Text conditional generative models and latent diffusion frameworks enable high customization and address creative and cultural nuances.

In addition, EMS [16] and the text-conditioned generative model of 3-D strand-based human hairstyles [17] (see Fig. 11) are examples of domain-specific tools which enables detailed features, such as eyebrows and hairstyles. Ash [30] (see Fig. 10), Avatarrex [31], and Poxture [32] highlight multiview video capture, customizable textures, and real-time rendering. For example, Poxture [32] combines the SMPL model with the U-net

architecture to achieve customizable textures, while Ash [30] improves the NeRF pipeline for real-time rendering.

Finally, DreamFace [15], AvatarStudio [19] (see Fig. 12), and Promptify [24] allow the use of natural language descriptions to refine character features, thereby reducing technical barriers. Systems such as EmoG [10] and Avatarrex [31] provide real-time feedback for agile workflows, thereby reducing iteration cycles. These AI technologies better highlight cultural differences between characters, allowing them to resonate more effectively with global users [12], [17]. We provide detailed data in the Supplementary Material.

C. Character Props and Garment Design

1) *How GenAI and LLMs Support the Creation of Character Props and Garments (RQ1)*: The integration of GenAI and LLMs offers significant advantages in terms of ease of use and customization flexibility, such as GenAI proposed by Forouzandehmehr et al. [33] and He et al. [36], which shows how GenAI and LLMs can streamline costume and prop design by providing text-driven inputs for generating cohesive and culturally relevant costumes. Forouzandehmehr et al.’s [33] (see Fig. 13) approach uses Llama2 to generate costume concepts and Stable Diffusion XL (SDXL) to convert textual descriptions into photorealistic images, enabling designers to customize character costumes based on name, age, and gender. Moreover, for prop design, Pixelor [39], and other systems generate basic sketches from natural language descriptions and optimize sketch clarity with the Seq2Seq Wasserstein autoencoder. In addition, LLMR [45] facilitates the creation of interactive props, enabling designers to use simple prompts to generate fully animated assets, such as “a glowing sword.” These tools reduce manual workload and enable faster prototyping, making prop modeling simpler and easier to iterate.

GenAI and LLMs also provide significant advantages in automating tasks and improving efficiency. For example, Dress-Code [36] allows natural language adjustments so that costumes

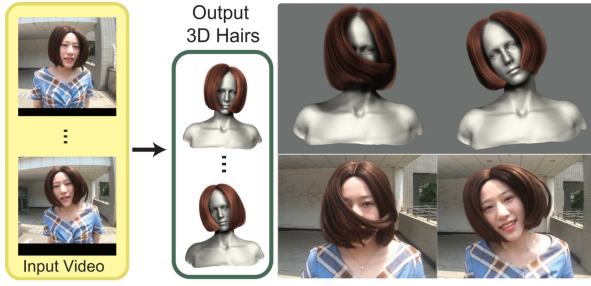


Fig. 14. Input video frames are processed to produce dynamic hair models (Figure reproduced with permission from [47]).

can be created in minutes and Sewformer can handle 68% of designs autonomously without intervention [34]. Similarly, Pixelor achieves an early recognition efficiency score of .715 [39].

2) *Current Limitations of GenAI and LLMs Supporting the Creation of Character Props and Garments (RQ3)*: However, limitations still exist, such as gender bias in garment generation [33], difficulties in processing complex seam connections [34], and limitations in rendering multilayer styles [36]. In addition, the AI frameworks of Liu et al. [35], and Chen et al. [37] may not be able to accurately model the input content when recognizing the input content due to the cross-points of the body detail parts or the input garments having occluded areas. For prop generation, Control3D may be distorted without accurate sketches, while LLMR relies on external APIs and can lead to unpredictable output content [45].

3) *Core AI Technologies and Overall Trends in GenAI and LLMs Supporting the Creation of Character Props and Garments (RQ2)*: The core technologies that appeared in the AI frameworks of the cited articles include Transformer-based LLMs (e.g., Llama2), diffusion models (e.g., SDXL, 3DStyle-Diffusion [43]) and GAN-based frameworks (e.g., Pixelor [39]). For 3-D clothing generation, tools, such as Sewformer, use neural networks to reduce errors in panel stitching [34] and DressCode uses CLIP⁸ models for semantic alignment [36]. For prop generation, Control3D integrates NeRF for accurate multiview rendering [40]. A notable trend is the increasing reliance on multimodal AI frameworks that combine text, image, and 3-D inputs to improve flexibility and output quality. These technologies are reshaping the workflows by lowering technical barriers, inspiring creativity, and accelerating the design process. We provide detailed data in the Supplementary Material.

D. Character Behavior and Animation

1) *How GenAI and LLMs Support the Creation of Character Behaviors and Animations (RQ1)*: GenAI can enhance game character behavior and animation design by improving realism, efficiency, and customization. Mask R-CNN can bridge 2-D sketches and animations, simplifying the transition from pictures to animations [46]. In 3-D modeling, HairSpatNet and HairTempNet leverage spatial and temporal motion analysis for dynamic hair animation (see Fig. 14) [47], while GAN-based models, such as Wasserstein GAN, with gradient penalty ensure natural eyes gaze animation [48]. GPT-3.5 integrates laban movement analysis and facial action coding system to generate animations [49] consistent with character-specific emotional and personality cues (see Fig. 15). Other tools like Pose2Pose [56]



Fig. 15. Utterances and their corresponding facial expressions generated by GPT-3.5. (Figure reproduced with permission from [49]).



Fig. 16. “Results of body part-level style control. A set of style prompts are applied to different body parts to achieve fine-grained style control.” (Figure reproduced with permission from [62], caption quoted verbatim).

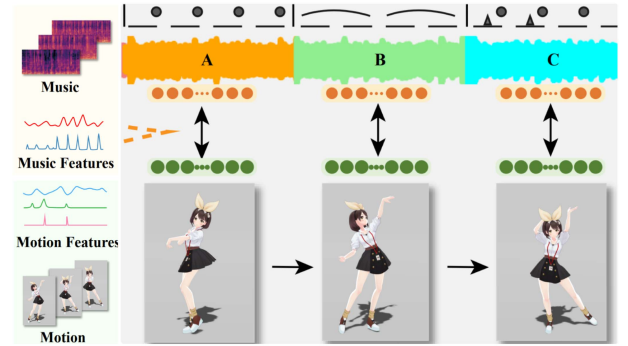


Fig. 17. “ChoreoMaster comprises two choreography-oriented modules: a choreomusical embedding module to capture music-dance connections, and a graph-based motion synthesis module to generate high-quality dance motions, following various choreographic rules, from input music.” (Figure reproduced with permission from [51], caption quoted verbatim).

and Bodyformer [57] enable semantically consistent gestures and synchronized animations, leveraging multimodal input sources, such as video, speech, and text. In addition, frameworks, such as PADL [60] and Gesturediffuclip [62], allow designers to manipulate 3-D character behaviors using natural language commands, supporting iterative prototyping and detailed customization (see Fig. 16). These frameworks demonstrate the ability of GenAI and LLMs to automate complex design tasks while maintaining the flexibility of designer-driven refinement.

Other advantages include enhanced scalability, reduced manual effort, and higher fidelity, for example, ChoreoMaster [51] (see Fig. 17) and Bailando++ [52] simplify the creation of dance animations by sharing latent space and choreography memories for beat accuracy and temporal coherence. CSTalk [53]

⁸CLIP (Contrastive Language–Image Pre-training): <https://openai.com/index/clip/>

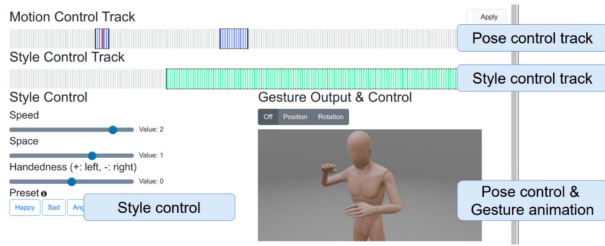


Fig. 18. UI of Sgtoolkit. (Figure reproduced with permission from [59]).

and EMOTE [54] support lip synchronization and emotional expression through parametric control, reducing technical barriers and improving production efficiency. SGToolkit [59] (see Fig. 18) and PADL [60] provide multimodal analysis and real-time animation capabilities, allowing for precise adjustment of gesture parameters. Bodyformer [57] and Rhythmic Gesture Generator [58] align gestures with speech rhythms to create realistic animations that enhance characters' interactions. These frameworks also replaced expensive motion capture technology, allowing small-scale game studios to produce high-quality character animation.

2) *Current Limitations of GenAI and LLMs Supporting the Creation of Character Behaviors and Animations (RQ3)*: The technical limitations of these GenAIs are also apparent, such as image-based segmentation methods, such as Mask R-CNN, have difficulty processing complex graphics and low-quality inputs [46], while HairSpatNet, which is limited by the low volumetric mesh resolution, which prevents the rendering of finer details [47]. Gaze models based on Wasserstein GAN lack advanced directional control for eye models and have difficulty combining gaze behavior with semantics, thus limiting their effectiveness in dynamic interactions [48]. Similarly, emotion animation tools, such as CSTalk, are often unable to capture subtle mood changes or adapt to fast and nonrhythmic speech patterns [53]. Cultural and stylistic diversity is another challenge, as reliance on narrow datasets, such as TED Talks and ZeroEGGS, reduces the ability of frameworks like PADL and Rhythmic Gesture Generator to express different emotions and behaviors [58], [62]. Real-time applications also face technical barriers, including high latency in generating complex actions and difficulty in processing noisy input, further complicating usability in interactive environments [58], [61]. These limitations emphasize the need for enhanced dataset diversity, improved computational efficiency, and more comprehensive integration of multimodal input to satisfy the growing demands of different use cases.

3) *Core AI Technologies and Overall Trends in GenAI and LLMs Supporting the Creation of Character Behaviors and Animations (RQ2)*: Transformer-based models, such as GAN, diffusion models, and reinforcement learning are the most common core technologies. For example, the Transformer in tools, such as CSTalk [53] and EMOTE [54], can align speech and animation with high accuracy. At the same time, GAN can drive natural gaze behavior and dance movements [48], [51]. Hu et al. [63] demonstrated diffusion models for stylized movement adaptation by adjusting noise levels [64]. The reinforcement learning framework used by Won et al. [64] applied the mixture-of-experts model to complex action categories, ensuring behavioral richness and physical realism. In addition, Pose2Pose [56] combined clustering algorithms and OpenPose for smooth motion transitions, while Bodyformer [57]

uses variational inference and positional embedding for realistic gestures. In general, GenAI is enabling high-quality character design, making advanced animation capabilities accessible to game studios of all sizes while significantly reducing reliance on traditional motion capture techniques. These trends highlight the potential of AI to drive innovation, cultural inclusion, and immersive storytelling in game design. We provide detailed data in the Supplementary Material.

VI. DISCUSSION

A. Bias, Risks, and Policies (RQ3)

Although GenAI can enhance the workflow of game character design, it also simultaneously introduces and even amplifies bias. Cheong et al. [66] observed that these models tended to select white males when generating characters or occupations of higher social status while perpetuating stereotypes of women and minority groups. Similarly, Liu et al. [67] reported that AI trained on Western-centered datasets distorts the representation of communities in the global South, causing cultural oversimplification and even inauthenticity [67]. To address these issues, mitigation strategies, such as self-contrastive fine-tuning, have been developed to train models on different datasets to achieve a more balanced and refined representation [67].

However, NPCs connected with GenAI and LLMs present additional challenges, including risks of generating hallucinations, spreading misinformation, and engaging in manipulative behaviors, such as promoting microtransactions [68]. Sas [68] emphasized the need to implement protective measures, such as reinforcement learning with human oversight to ensure ethical AI behavior and minimize unintended consequences. Ethical frameworks, such as the AI Act,⁹ stress the importance of transparency, accountability, and robust risk management. To this end, developers must employ technical safeguards and organizational policies to promote responsible AI use, protect user privacy, and prevent unethical practices.

B. Impact on Traditional Design and Art Industries (RQ3)

Maden et al. [69] emphasized that GenAI and LLMs are causing a serious impact on the traditional art and design industries, noting widespread professional skill obsolescence and increased competition for emerging artists struggling against AI-generated content. Jiang et al. [70] raised ethical concerns about the unauthorized use of artists' works to train AI models, leading to financial repercussions for original creators. Ko et al. [3] pointed out that AI-generated content often lacks true creative innovation due to the inherent limitations of pre-trained models. Consequently, while GenAI and LLMs boost efficiency, the design industry must carefully balance AI-driven methods with the preservation of human creativity, cultural richness, and artistic integrity.

C. Impact of AI Guardrails on Character Design (RQ3)

Implementing guardrails in GenAI presents the dual challenge of balancing the requirements of safe, responsible content generation with maintaining creative flexibility. For example, the inability to generate content for "evil" or "problematic" characters limits the creative scope of character designers. Dong et al. [79] suggested that whilst guardrails are essential to ensure

⁹EU Artificial Intelligence Act: <https://artificialintelligenceact.eu/>

safe operation, they can also limit the depth of exploration of the model, resulting in a response that is too simple to support creative narrative generation. Bender et al. [80] reported that overly strict filtering mechanisms not only limit creative output, but may also suppress valuable content. Their analysis suggests that while strict content review is essential to mitigate harmful output, it may inadvertently suppress certain narratives. Thus, achieving an effective balance between upholding ethical standards and fostering creative outcomes remains an open research challenge.

D. Sustainable AI Development (RQ3)

Recent evidence suggests that the development of AI poses significant environmental challenges. Bender et al. [80] reported that while the average human emits around five tonnes of carbon dioxide annually, training a Transformer model using neural architecture search is estimated to generate 284 tonnes of carbon dioxide. Furthermore, training a single BERT base model consumes as much energy as a trans-America flight. Additionally, research by Li et al. [81] found that substantial water resources—around 700,000 liters—are consumed when training GPT-3 in data centers operated by Microsoft in the U.S. They also forecasted that by 2027, global water usage from AI-related activities are expected to rise significantly, reaching 4.2-6.6 billion cubic meters. Collectively, these findings emphasize the urgent need for sustainable practices in AI development to mitigate its extensive carbon and water footprint.

E. Future Development (RQ3)

Current research on AI-assisted 3-D character creation remains limited. To address this, we draw on advancements in related fields, such as AI-assisted user interface (UI) design [3] and industrial design [71] to anticipate the potential future directions of GenAI in character creation. Enhancing collaboration between humans and AI, with a focus on optimizing team workflows, is likely to be a central priority. Advances in human-AI interaction (HAI) and computer-supported collaborative work (CSCW) are expected to improve integration, allowing design teams to collaborate more effectively and creatively. In addition, interactive prototyping, tailored fine-tuning, and specialized AI models will support more efficient, innovative, and culturally informed character design.

One limitation comes from the process of supporting character design conceptualization. Franson and Thomas [75] provided a comprehensive analysis of how gameplay and environmental contexts influence game character design, emphasizing that different types of games have unique aesthetic and functional requirements. Examples range from detailed character anatomy in first-person shooters to narrative-driven visual complexity in role-playing games. However, despite these important insights, our literature search revealed a lack of dedicated AI systems specifically designed to assist in the early conceptualization stages of character design. Such AI-driven approaches could simplify the ideation process by integrating game mechanics, character backstories, and environmental factors into coherent design recommendations, thereby enhancing visual consistency and accelerating prototype iterations. This gap highlights a key opportunity for future research, namely, that the development of AI-assisted conceptualization tools is likely to improve the efficiency and innovation of game character design efforts.

Another critical aspect that enhances the effectiveness of AI tools is improved visualization and adjustability. For instance, IntentTuner [23] captures the user's design intent and visualizes

it, enabling designers to fine-tune elements, such as appearance, clothing, or facial expressions, during content generation. This process improves the consistency between AI-generated content and the designer's vision while addressing challenges like cumbersome data augmentation (see Fig. 7) [23]. Real-time feedback and continuous evaluation features reduce iteration fatigue, ultimately boosting productivity and ensuring higher quality outcomes.

Furthermore, integrating multiple input modes represents a transformative direction for AI. Li et al. [71] demonstrated how these advances allow designers to use text, images, and even 3-D models as input prompts, facilitating a more flexible and interactive dialogue between the AI system and users. This capability enables GenAI to produce visually and conceptually coherent design prototypes, while features like "prompt bibliographies" help team members systematically track design iterations, enhancing organization and efficiency across the design workflow.

In addition, Sketchar¹⁰ has been transformative in bridging the gap between conceptualization and visual design at different steps of the design workflow. By providing immediate visual feedback and translating textual descriptions into visual prototypes, Sketchar overcomes communication difficulties within interdisciplinary teams (see Fig. 6) [5]. This AI tool optimizes collaboration in game development teams by reducing misunderstandings, minimizing extensive communication, and streamlining revision efforts.

Finally, as the game industry and design objectives become increasingly complex, AI assistants will require specialized models trained in areas such as art concepts, behavioral analysis, and 3-D modeling across all stages of the character design workflow and increase the flexibility and accuracy of the AI tools [3]. As proposed by Liapis et al. [82], the different stages of character design can be generated by different specific systems and then combined. This would allow for precise refinement and control while obtaining high quality outcomes at each step of the process.

F. Overall Implications

The findings of this study have significant implications for both the game and AI development communities. GenAI integration into design workflows redefines processes by simplifying complex tasks, such as prototyping and iteration, while improving collaboration between designers, developers, and stakeholders. However, along with increased efficiency, designers are losing control over the design orientation of their work, and creative control is a key factor in maintaining the authenticity and vision of human designers. The adoption of GenAI is transforming industry skill sets, requiring designers to have the ability to interpret and refine AI-generated content. Moreover, understanding the principles and workflows that can best facilitate the use of GenAI enables designers and developers to make the most of its potential while being aware of its limitations and emergent trends.

G. Overall Recommendations

For GenAI developers, it is crucial to enable designers to achieve their intended outcomes more accurately by expanding the variety of input methods and improving the controllability of AI-generated outputs. Additionally, as highlighted in Zhu

¹⁰Sketchar: <https://sketchar.io/>

et al. [78] in their work on explainable AI, ensuring that AI and machine learning systems can clearly communicate the rationale behind generated content enhances designers' trust and facilitates informed refinements. Developers should also prioritize cultural sensitivity and ethical integrity by diversifying training datasets to minimize biases. Ultimately, making GenAI tools more versatile and capable of supporting additional stages within the design workflow will significantly enhance overall efficiency.

For designers, GenAI should primarily be used as a supportive tool, preserving the fundamental creative direction within human control. It is essential that designers actively engage in the development and testing of GenAI tools, providing critical feedback as end users. To craft realistic, culturally nuanced characters, designers must draw upon their expertise in fields such as history, culture, body language, and micro-expressions—areas where GenAI may fall short due to inherent biases or limitations within its training data. While GenAI can streamline workflows and support technical processes, it cannot substitute the nuanced understanding that human designers contribute. Furthermore, the design industry should advocate for policies to address challenges related to originality and copyright protection, acknowledging the complexities involved in safeguarding intellectual property in the era of AI.

VII. LIMITATIONS

This study has several limitations. First, while this review focused on studies published between 2019 and October 2024, the rapid pace of technological advancements in GenAI and LLMs means that very recent innovations may not be captured. Second, despite adherence to the PRISMA methodology, the study selection process may have been influenced by the reliance on five specific databases and the limitations of the chosen keywords and search strategy.

Third, the review excluded nonacademic sources, such as industry reports and blogs, to maintain a focus on peer-reviewed content. Especially, we excluded commercial platforms because they do not explicitly disclose their core technologies, processing methods, or quantitative data—such as generation speed during peak usage times or variations in output quality—as academic papers do. This poses significant challenges for our research and verification process. Moreover, due to the rapid advancement of GenAI, emerging policy regulations or restrictions could impact the continued relevance or accuracy of this paper. In contrast, academic research provides more stable references. For example, an increasing number of governments worldwide are discussing banning DeepSeek¹¹ for security reasons. We aim to ensure that the analysis in this article remains relevant and does not become outdated or unusable due to external changes.

Finally, while we categorized GenAI applications based on design workflows and input–output modes, these categorizations may not fully align with the diverse needs of specific industry groups, as the challenges and resource constraints faced by large game studios and independent developers differ significantly.

VIII. CONCLUSION

While there are ethical challenges to using GenAI and LLMs in character creation, the creative benefits and reduced overhead are significant. GenAI and LLMs enhance creativity and efficiency, lower technical barriers, and are especially valuable for

small studios and indie developers. They enable designers and developers to quickly generate prototypes and assets, fostering rapid cocreative innovation. Moving forward, developing HAI workflows is essential. Advances in HAI and CSCW technologies can help overcome constraints while preserving cultural relevance and artistic integrity. Furthermore, integrating customized AI models, interactive prototyping tools, and ethical, culturally respectful practices will promote greater inclusivity and accessibility in character creation.

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¹¹DeepSeek: <https://deepseek.com/>

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