

Review

The Impact of AI on Game Development: A Scoping Review of Transformations, Career Implications, and Emerging Challenges

Yongkang Xing ¹, Jethro Shell ², Tracy Harwood ³, Conor Fahy ², Hongji Yang ⁴, Shengxiang Yang ², Kun Chen ¹ and Guokai Feng ^{5,*}

¹ School of Digital Media and Interactive Design, Guangzhou Maritime University, Guangzhou 510725, China; xingyongkang@gzmtu.edu.cn (Y.X.); chenkun@gzmtu.edu.cn (K.C.)

² School of Computer Science and Informatics, De Montfort University, Leicester LE1 9BH, UK; jethros@dmu.ac.uk (J.S.); conor.fahy@dmu.ac.uk (C.F.); syang@dmu.ac.uk (S.Y.)

³ School of Digital Media and Interactive Design, De Montfort University, Leicester LE1 9BH, UK; tharwood@dmu.ac.uk

⁴ School of Computing and Mathematical Sciences, University of Leicester, Leicester LE1 7RH, UK; hy124@leicester.ac.uk

⁵ School of Credit Management, Guangdong University of Finance, Guangzhou 510521, China

* Correspondence: fengguokai@gduf.edu.cn

Abstract

Artificial intelligence (AI) is increasingly transforming the game industry by reshaping development processes, production workflows, and career structures. In this study, we present a scoping literature review examining the impact of AI on game development and employment within the industry, with particular attention to the perspectives of displacement, task transformation, and productivity effects. Drawing on academic research and industry reports published between 2020 and 2026, while retaining earlier foundational literature where relevant, this study analyzes how AI technologies such as generative AI, machine learning, procedural content generation, and large language models are integrated across major stages of game production, including game art, production management, programming, and live operations. Our findings indicate that AI can support efficiency, accelerate development cycles, and enable new forms of personalization and creative experimentation. At the same time, AI adoption may alter workforce dynamics by increasing the automation potential of routine and entry-level tasks, especially in areas such as asset creation and quality assurance. Rather than fully replacing workers, however, AI more commonly reconfigures job roles and increases demand for hybrid skill sets that combine technical knowledge, creativity, and AI literacy. Our study also identifies emerging opportunities in AI-assisted design, data analytics, and machine learning integration. Despite these benefits, AI adoption introduces important challenges related to employment polarization, intellectual property, workforce adaptation, ethical governance, and market concentration. We conclude that AI is fundamentally reshaping the game industry and highlight the need for balanced strategies that support innovation while preserving creative diversity, sustainable career pathways, and equitable access to technological opportunities. Overall, the strongest evidence concerns AI capabilities, workflow changes, and task-level transformation, whereas direct evidence of actual employment outcomes and long-term occupational change remains limited and uneven.

Keywords: AI; Game Development; creative industry; employment



Academic Editor: Carlos Vaz de Carvalho

Received: 13 August 2026

Revised: 3 October 2026

Accepted: 8 October 2026

Published: 9 October 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article

distributed under the terms and

conditions of the [Creative Commons](#)

[Attribution \(CC BY\)](#) license.

1. Introduction

1.1. Background

Artificial intelligence (AI) has rapidly evolved into a foundational technology within the global digital economy, reshaping how industries create, innovate, and deliver value [1,2]. Among these industries, the game sector stands out as a particularly dynamic and transformative domain situated at the intersection of advanced technology, creative production, and interactive user engagement [3]. In recent years, advances in machine learning, natural language processing, and generative AI have accelerated the integration of AI into core stages of game development, contributing to an increasingly integrated role within production workflows [4,5].

Across the game development lifecycle, AI is increasingly embedded in both creative and technical processes. In pre-production, generative AI tools support concept art generation, narrative ideation, and character design, enabling rapid prototyping and creative experimentation [6]. During production, procedural content generation (PCG) techniques allow developers to algorithmically create environments, levels, and assets, reducing development time while enabling large-scale and dynamic game worlds [7]. AI-driven animation, physics simulation, and behavior modeling further enhance realism and interactivity. In post-launch phases, AI-powered analytics and machine learning systems enable the real-time monitoring of player behavior, facilitating personalized experiences, adaptive gameplay, and data-driven monetization strategies [8].

These developments are not only transforming how games are made but are also reshaping career pathways and skill requirements within the industry. Traditional roles such as artists, designers, and testers are increasingly supported by AI tools, altering workflows and productivity expectations [5]. At the same time, new roles are emerging, including AI-assisted designers, data analysts, and machine learning specialists [9]. This dual process of augmentation and transformation reflects a broader shift toward hybrid skill sets that combine technical expertise with creative capabilities.

The growing adoption of AI in game development also introduces a complex set of challenges. Concerns have emerged regarding the potential displacement of certain roles, particularly in areas such as asset creation and quality assurance, where automation can substitute for repetitive or standardized tasks [10,11]. In addition, issues related to intellectual property, ethical use of generative AI, and the quality and originality of AI-generated content are becoming increasingly prominent [12]. These challenges highlight the need to critically assess not only the benefits of AI, but also its broader implications for creative work and professional identity in the industry.

At the same time, AI presents significant opportunities for innovation and industry growth. By reducing production costs and lowering technical barriers, AI enables smaller studios and independent developers to participate more actively in game creation [13]. It also facilitates the development of new game genres and experiences, such as personalized and adaptive gameplay systems, which were previously difficult to implement [14]. Furthermore, AI-driven tools can enhance cross-disciplinary collaboration, enabling more efficient workflows and fostering new forms of creativity.

The impact of AI is particularly evident in major gaming markets such as China, where rapid technological adoption, strong industry growth, and supportive policy environments have accelerated the integration of AI into development practices [15,16]. Chinese game companies are actively investing in AI technologies to enhance competitiveness, improve efficiency, and expand global reach [17]. This context provides valuable insights into how AI reshapes both production processes and career structures within a large and rapidly evolving market.

Overall, AI is driving a fundamental transformation in the game industry, influencing how games are developed, how professionals work, and how value is created. However, its impact is multifaceted, involving both opportunities for innovation and challenges related to workforce adaptation, ethical considerations, and industry structure. Existing reviews have examined several important aspects of artificial intelligence in creative and game-related contexts. For example, Amankwah-Amoah has discussed the opportunities, challenges, and research agenda associated with generative AI across creative industries [18]. Additionally, Stige has provided a systematic review of AI applications in UX design [19], while Lao has reviewed AI-driven game design and user experience research [20]. While these studies provide important foundations for understanding AI-enabled creativity, design practices, and user experience, their primary emphasis differs from the focus of the present review. In particular, the relationship between AI-enabled development tasks, changing work practices, and career implications in the game industry has not been examined in a unified evidence synthesis. Therefore, in the present study, we review AI applications across game development activities and examine their potential implications for work organization, skills, and career pathways.

1.2. Research Questions

In light of these developments, we adopt a review-based approach to examine the evolving role of AI in the game industry, with a particular focus on development processes, career implications, and emerging challenges and opportunities. Specifically, we address the following research questions:

First, how is AI transforming the game development process across different stages of production? This question explores the applications of AI in pre-production, production, and post-launch operations, highlighting how these technologies reshape workflows and creative practices.

Second, how does AI influence career pathways and skill requirements in the game industry? This includes examining both the displacement of traditional roles and the emergence of new, AI-related occupations, as well as the growing importance of interdisciplinary skill sets.

Third, what are the key challenges and opportunities associated with AI adoption in game development? This question considers issues such as job displacement, ethical concerns, and intellectual property, alongside opportunities for innovation, efficiency gains, and industry expansion.

By addressing these questions, we provide a comprehensive overview of AI's impact on the game industry, offering insights into how technological change is reshaping both development practices and professional landscapes.

2. Methodology

This study adopts a scoping review approach to synthesize existing research on the impact of AI on game development, career pathways, and associated challenges and opportunities. A scoping review was selected because the literature spans diverse research designs and evidence types, covering both technological applications and broader employment and career implications. This approach allows us to map the existing evidence base and identify major themes, trends, and research gaps without restricting the analysis to a narrowly defined intervention or outcome.

2.1. Search Strategy

To address the research questions, a literature search was conducted across academic databases relevant to AI, game development, and digital production, including Google Scholar, Scopus, Web of Science Core Collection, and IEEE Xplore [21,22]. The search

was conducted between 1 June 2026 and 15 June 2026. The database-specific search dates, search fields, complete search strings, applied filters, and numbers of retrieved records are reported in Table A1 in Appendix A.

The search strategy was developed around three complementary areas. The first concerned AI and its relationship with game creative industries; the second focused on AI applications across game production and development workflows, including asset creation, game design, programming, operations, content pipelines, and level design; and the third addressed employment and career-related implications, including task substitution, occupational transformation, changing skill requirements, workforce adaptation, and emerging employment opportunities.

These conceptual search areas were translated into database-specific Boolean strategies to accommodate differences in search syntax and field definitions. Scopus, Web of Science Core Collection, and IEEE Xplore searches used title, abstract, and keyword fields where supported. Google Scholar was searched using combinations of the same conceptual terms, because its interface does not provide equivalent field-level Boolean controls.

In addition to database searching, backward and forward citation tracking was used to broaden coverage and reduce the risk of missing relevant publications. Backward searching involved examining the reference lists of relevant sources to identify earlier studies and theoretical work, while forward searching used cited-by functions to identify subsequent publications building on the retrieved evidence.

Supplementary web searches were also conducted using Google Search to identify relevant websites and technical reports that were not indexed in the academic databases. Searches combined terms related to AI, game development, employment, careers, and industry reports. The searches were conducted during the same review period (1 June 2026 to 15 June 2026), and the retrieved sources were screened using the same relevance and source-quality criteria as other records. This process resulted in 15 website records and 12 technical reports from organizations or corporations, as reported under “other methods” in Figure 1.

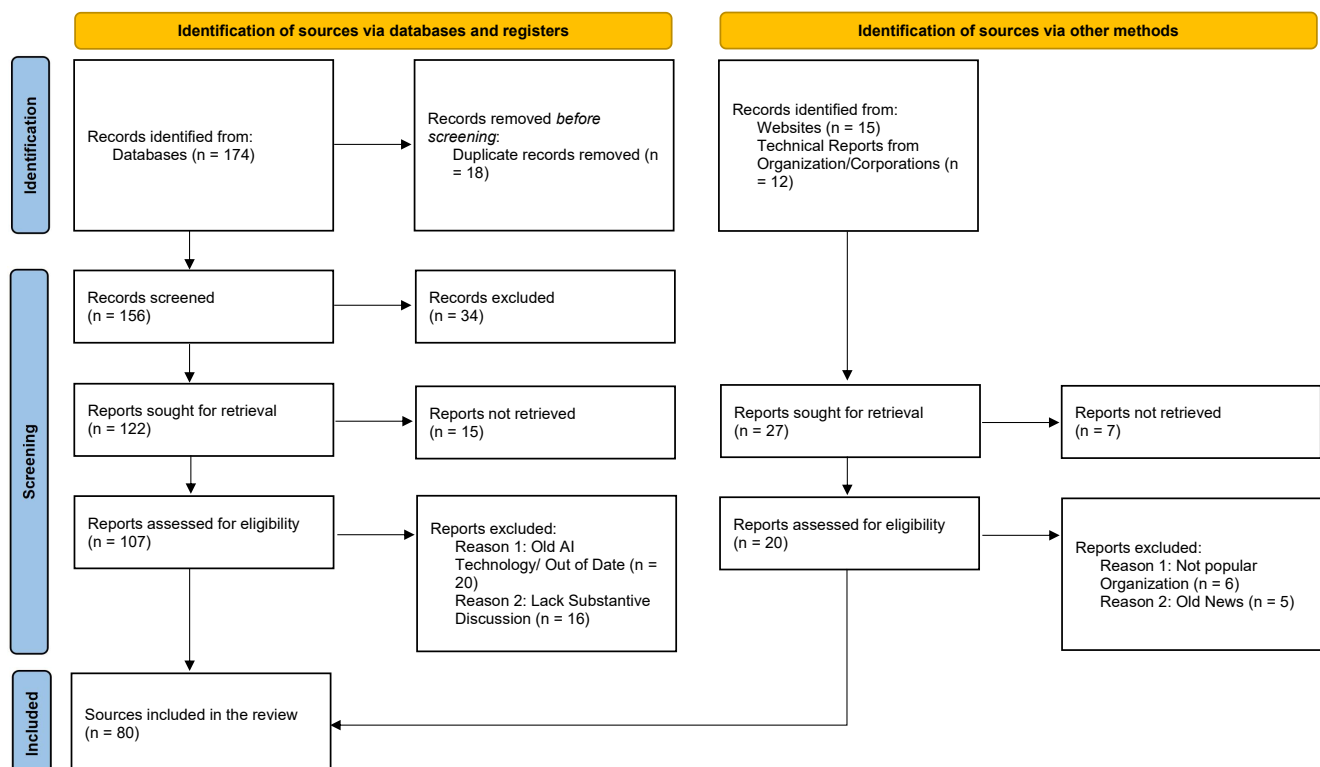


Figure 1. PRISMA study selection flow diagram.

2.2. Screening and Eligibility

The study selection process followed a multi-stage procedure and was documented using a PRISMA 2020 flow diagram. The flow diagram reports the numbers of records identified, screened, excluded, and retained from databases and registers and from other search methods (Figure 1). The PRISMA 2020 checklist is in Supplementary Material.

After duplicate records were removed, titles and abstracts were screened to identify potentially relevant records. Full texts were then assessed against the predefined eligibility criteria. Sources identified through backward and forward citation tracking were assessed using the same criteria. Screening decisions were based on the substantive relevance of each source to the review questions and on the transparency and adequacy of the evidence provided.

Screening and data extraction were conducted independently by two reviewers using the predefined eligibility criteria and structured extraction form. Before the formal screening and extraction stages, the reviewers conducted a calibration exercise on a subset of records to establish a consistent interpretation of the eligibility criteria and extraction fields. Disagreements identified during the calibration exercise and subsequent screening or extraction were resolved through discussion and consensus. Data extraction was independently performed by both reviewers, and discrepancies were checked against the original sources and resolved through discussion and consensus. The review primarily targeted publications from 2020 to 2026 to reflect recent developments in generative AI and machine learning; however, earlier foundational theories, reviews, or future-oriented employment studies were retained where they were essential to framing the research questions (Table A3).

The eligibility criteria were as follows.

- **Outdated/Old News:** Sources were considered outdated when the underlying AI technology or capability had been substantially superseded by newer generations, so the reported findings no longer represented contemporary AI practices in game development. Publication date alone was not used as an exclusion criterion. We retained older sources when they provided foundational theoretical or conceptual value.
- **Insufficient Methodological Detail:** Assessed according to source type. For empirical studies, sufficient information concerning study design, data/sample, data collection, and analysis was required; for industry reports, sufficient information was required to assess the basis of reported estimates, surveys, or conclusions.
- **Reputable Industry and Media Reports:** Reports published by recognized national or international organizations, established industry associations, major AI technology or model companies, universities and their academic workshops, research institutions, government or intergovernmental bodies, and established media organizations. Reports were considered reputable when their source, authorship, publication process, and supporting evidence were identifiable and traceable. Conversely, sources with unclear provenance or authorship, unsupported claims, insufficient methodological detail, or predominantly promotional intent were considered non-reputable institutions/organizations.

2.3. Data Extraction and Synthesis

To avoid conflating substantive evidence with the supporting literature, the retained references were classified into four categories according to their role in the review:

- **Evidence sources**, which directly addressed AI applications in game development, employment, skills, or career implications and were subjected to data extraction and thematic synthesis;

- **Methodological references**, which were used to justify the search, screening, and review procedures;
- **Foundational literature**, which provided established theoretical and conceptual perspectives, particularly on automation, technological change, and labor market transformation;
- **Contextual sources**, which provided supplementary industry, technological, policy, or broader contextual information.

Data extraction therefore focused specifically on the evidence sources, covering study methodology, key findings, and reported implications related to AI, game development, employment, skills, and careers, as presented in Table A2 and Figure A1. Methodological references, foundational literature, and contextual sources were retained to support the review methodology, conceptual framework, and interpretation of the findings, respectively, but were not treated as substantive evidence in the thematic synthesis. Because the evidence sources varied considerably in study design and evidence type, quantitative meta-analysis was not appropriate; instead, qualitative thematic synthesis was used to integrate findings across disciplines and publication formats. Accordingly, the PRISMA flow diagram reports the records retained in the review corpus, while Table A2 explicitly identifies the role of each retained reference. Only references classified as evidence sources were treated as the primary corpus for substantive evidence synthesis, whereas methodological, foundational, and contextual references served as the supporting literature and were not treated as independent empirical evidence.

Within the evidence sources, we listed Adjacent domain/Extrapolative evidence. Adjacent domain/Extrapolative evidence addressed related phenomena in other domains, such as software engineering, project management, architecture, engineering, education, or the wider creative industries. These sources were retained but mark 'Adjacent domain/Extrapolative' when they provided relevant evidence for interpreting potential implications for game development, but their findings were not treated as direct evidence of outcomes in the game industry.

Because the evidence sources varied considerably in study design and evidence type, quantitative meta-analysis was not appropriate. Instead, qualitative thematic synthesis was used to integrate findings. We distinguished evidence from well-supported empirical studies from conceptual arguments, descriptive reports, technical documentation, and first-party industry claims. The latter sources were used to identify emerging practices, reported industry developments, or potential effects, but were not treated as equivalent to independently generated empirical evidence.

Accordingly, the PRISMA flow diagram reports the records retained in the review corpus. Only references classified as evidence sources formed the primary corpus for substantive evidence synthesis, while methodological, foundational, and contextual references served as the supporting literature. During synthesis, claims were also checked against the role and domain of their cited sources. Where direct game-industry evidence was unavailable, adjacent-domain evidence was retained but explicitly identified as contextual or extrapolative rather than as direct evidence of game-industry outcomes. The extracted evidence was then organized into four topics: AI-driven transformation of work; AI applications in game development processes; career implications and skill shifts; and challenges and opportunities associated with AI adoption.

3. AI and the Transformation of Work

The impact of AI on work and employment has been widely discussed across multiple disciplines, particularly within labor economics and innovation studies. To analyze these dynamics, the literature typically adopts three complementary perspectives based on Ace-

moglu's study; namely, displacement, task transformation, and productivity effects [23]. Acemoglu indicated that these perspectives provide a structured framework for examining how technologies reshape labor markets, whether by substituting for human labor, reconfiguring the content of work, or generating new economic opportunities [23]. They can additionally capture different mechanisms through which AI influences employment outcomes. Therefore, we use these perspectives to construct a better understanding of the interconnected dimensions of AI technological change, as shown in Figure 2.

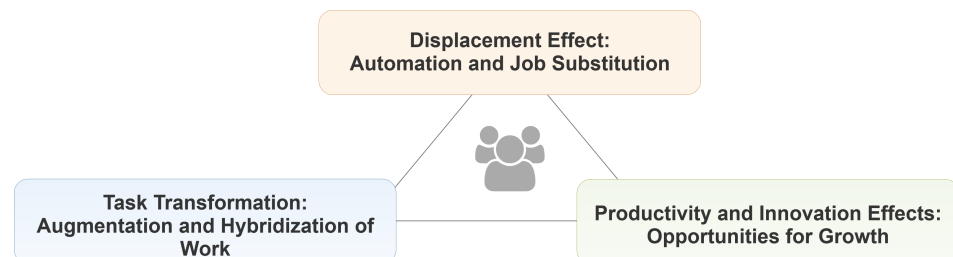


Figure 2. Three perspectives on AI and the transformation of work.

3.1. Displacement Effect: Automation and Job Substitution

The displacement effect emphasizes the potential of automation technologies to substitute for human labor, particularly in routine and codifiable tasks. This perspective builds on earlier work in automation and technological change, most notably the routine-biased technological change (RBTC) framework, which argues that technologies disproportionately replace middle-skill routine jobs while leaving non-routine tasks relatively unaffected [24]. Before the wave of AI technologies, Frey and Osborne (2017) had already estimated that a significant proportion of jobs were at risk of automation, extending these concerns to AI-enabled systems capable of performing both manual and cognitive tasks [25]. Subsequent research has provided further evidence that some of these automation-related concerns may extend to AI-enabled systems. Several studies have suggested that machine learning systems can automate not only manual labor but also certain cognitive tasks, thereby expanding the scope of potential displacement [26,27].

In game creative industries, this assumption has historically been less prominent due to the non-routine nature of creative work [28,29]. However, recent advances in generative AI challenge this notion. Tools capable of producing images, animations, and written content have begun to automate aspects of creative production, particularly in areas such as illustration and asset design [10,12]. This suggests that even creative roles may be partially susceptible to automation when tasks can be standardized.

At the same time, the displacement effect is not uniform across all workers. Lower-skilled and entry-level positions are generally more vulnerable, as they involve tasks that are easier to codify and automate [30]. In contrast, high-skilled workers who perform complex, non-routine tasks are less likely to be replaced and may even benefit from AI adoption [30]. This uneven impact contributes to labor market polarization, where employment opportunities decline in the middle while expanding at the high and low ends of the skill distribution.

3.2. Task Transformation: Augmentation and Hybridization of Work

In contrast to the displacement perspective, the task-based approach offers a more nuanced view, viewing jobs as collections of tasks rather than fixed occupations [31]. From this perspective, AI may reconfigure jobs by automating specific tasks while complementing human capabilities in others. George argues that AI reshapes job content, enabling workers to focus on higher-value, non-automatable activities [32].

From this perspective, AI has been described as complementing human labor in a range of contexts [33]. Instead of replacing workers, it augments their capabilities by automating routine components of their tasks, allowing them to focus on higher-value activities [33]. In the game industry, Bezzina has indicated that AI tools can handle repetitive tasks such as asset generation and bug detection, freeing designers and developers to focus on the creative and strategic aspects of production [10]. This shift can increase productivity while also enhancing job quality.

The task transformation perspective is particularly relevant for understanding the impact of AI in game creative industries. Game development involves a complex interplay of artistic and technical tasks, many of which are difficult to fully automate. While AI can assist in generating visual assets or optimizing workflows, human input remains important, particularly for tasks such as storytelling, game design, and user experience [19]. As a result, rather than eliminating most jobs, AI is more likely to change the skill requirements associated with them.

This transformation often leads to skill upgrading, as workers are required to adapt to new technologies and develop complementary competencies. Game artists may need to learn how to use AI-assisted design tools, while developers may need to acquire knowledge of machine learning algorithms. While this process can create opportunities for workers who are able to adapt, it may also pose challenges for those who lack access to training or education.

3.3. Productivity and Innovation Effects: Opportunities for Growth

The productivity effect provides a more optimistic view on employment, emphasizing the role of technological innovation in driving economic growth and job creation [34]. According to this perspective, AI can increase efficiency and reduce production costs, potentially enabling firms to expand output and creating conditions for new employment opportunities [35,36]. This mechanism is consistent with classical economic theories of technological change, which argue that productivity gains ultimately lead to higher demand for labor.

Empirical evidence supporting the productivity effect can be found in studies that link AI adoption to firm performance and labor demand. In the game industry, AI-driven tools can reduce development time, allowing studios to produce more games or update existing titles more frequently [37]. This expansion of output can create additional demand for labor, particularly in areas such as marketing, operations, and customer support.

In addition, AI enables the creation of entirely new products and services, which can generate new markets and employment opportunities. In the gaming sector, innovations such as AI-generated content, personalized gaming experiences, and adaptive gameplay systems have opened up new avenues for development [14]. These innovations may increase demand for new types of expertise, although direct evidence of resulting job creation in the game industry remains limited [14].

However, the productivity effect is not automatic and depends on various factors, including market conditions, firm capabilities, and institutional support [38]. In highly competitive industries, productivity gains may lead to consolidation rather than expansion, limiting the potential for job creation. Fernández noted that, if the benefits of AI are concentrated among a small number of firms, the overall employment impact may be uneven [39].

4. Impact of AI on Key Roles in Game Development

The previous section examined the impact of AI on employment through three complementary theoretical perspectives—displacement, task transformation, and productivity effects—highlighting the complex and sometimes contradictory ways in which AI reshapes

labor markets. While these frameworks provide a useful conceptual foundation, their implications are more clearly understood when applied to specific industries. The game development sector offers a particularly relevant context, as it combines creative, technical, and managerial work that is increasingly influenced by AI technologies.

Building on this theoretical discussion, this section explores how AI is transforming employment across concrete professional roles within the game industry, focusing on key areas such as game art, game production, programming, and game operations. Through this perspective, we examine how mechanisms such as displacement, task reconfiguration, and productivity enhancement manifest in practice. This role-based analysis provides a more detailed understanding of how AI reshapes not only what work is done, but also how it is performed and what skills are required.

4.1. Game Art

One of the most visible applications of AI in game development is in game art and content creation. Generative AI tools are increasingly used to produce concept art, character designs, textures, and animations [6,10]. These tools allow artists to rapidly generate and iterate on visual ideas, reducing the time required for early-stage design. Instead of creating assets entirely from scratch, artists can use AI-generated outputs as a starting point and refine them according to artistic direction, as shown in Figure 3.

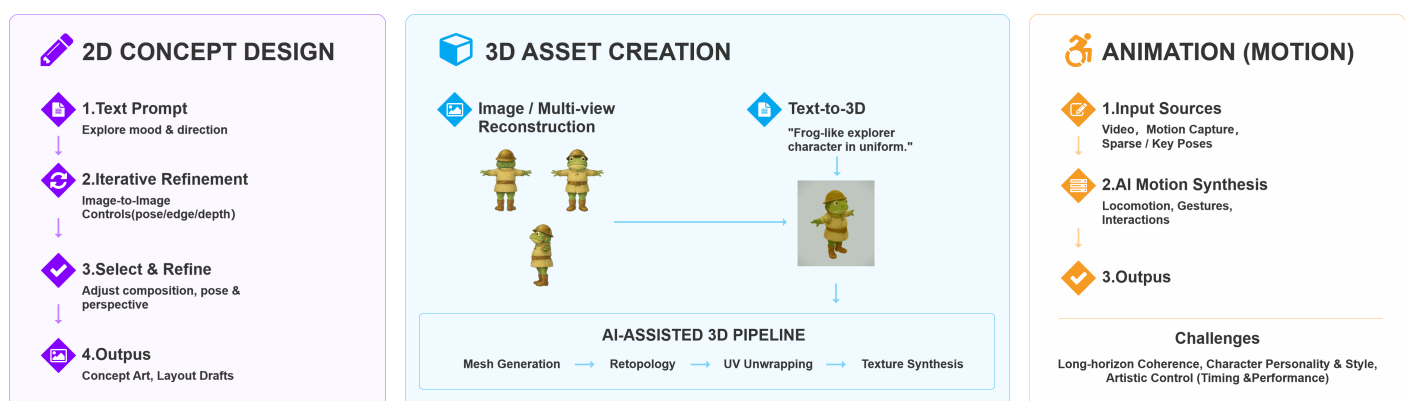


Figure 3. AI in game art pipeline.

In practical creative workflows, artists rarely rely on a single generation pass. Instead, they combine text-to-image/image-to-image models such as MidJourney and GPTImage to refine their results iteratively [40]. These models allow creators to anchor outputs to specific compositions, poses, depth cues, or perspective grids [40]. Illustrators can begin with a loose text prompt to explore mood and visual direction, then feed a selected output back into the model with pose constraints or edge maps to correct anatomy, adjust camera angles, or reinforce spatial coherence. This layered process positions AI generation as a more controllable production aid. As a result, AI-generated imagery is increasingly viable not just for inspiration but for early-stage assets such as concept sketches, storyboards, and layout drafts. It can enable rapid iteration across multiple design directions, styles, and compositions before committing to a final, fully realized piece.

Beyond 2D concept design, AI is rapidly expanding into 3D asset creation, reshaping how artists and technical designers approach modeling workflows. Tripo 3D, Hyper3D, and other models can reconstruct detailed 3D scenes or objects directly from multi-view image data, capturing lighting, depth, and material properties with impressive fidelity [41]. At the same time, emerging text-to-3D models can also enable creators to generate rough 3D meshes from simple textual descriptions [42]. For example, an artist might describe a "stylized sci-fi helmet with glowing edges," and receive a base model that can be further

refined in traditional 3D software. Furthermore, Tripo 3D streamlines key stages of the 3D pipeline, including automatic mesh generation, UV unwrapping, retopology, and texture synthesis [43], potentially reducing the time spent on repetitive technical tasks.

In animation, while machine learning is increasingly applied to motion synthesis and character rigging, its maturity still lags behind advances seen in 2D image generation and emerging 3D asset tools. A range of research-driven and early commercial systems such as DeepMotion Animate 3D and RADiCAL Motion [44,45] have demonstrated how AI can extract and generate motion data from video or sparse inputs [44]. Techniques based on motion capture datasets, along with recurrent neural networks and transformer-based architectures, enable the generation of believable locomotion, gestures, and character interactions [44]. However, compared to the relative maturity of 2D concept generation and the rapidly evolving space of AI-assisted 3D modeling, animation AI still faces notable gaps in commercial readiness. Challenges remain in maintaining long-horizon temporal coherence, preserving character personality and style, and ensuring precise artistic control over timing and performance. As a result, most studios continue to rely heavily on traditional pipelines, using AI primarily as an assistive layer rather than a full replacement.

4.2. Game Production

AI is also reshaping game production processes by improving coordination, planning, and resource management across increasingly complex development environments. Modern game projects often involve large, multidisciplinary teams distributed across different locations, making efficient production management both critical and challenging. In this context, AI-driven tools, particularly large language models (LLMs) such as ChatGPT and Gemini [46], are increasingly used to support early-stage concept development, communication, and cross-team alignment. These tools function not only as content generators but also as collaborative assistants that facilitate clearer and faster information exchange between departments, as shown in Figure 4.

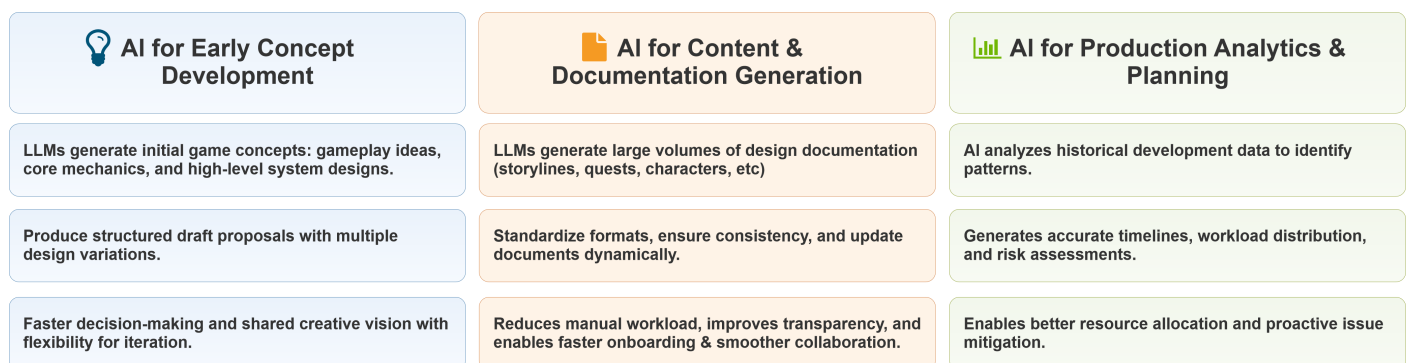


Figure 4. AI in game production.

Serra has indicated that LLMs can assist in rapidly generating initial game concepts, including gameplay ideas, core mechanics, and high-level system designs [47]. Instead of relying solely on iterative discussions between designers, writers, and producers, which can be time-consuming and subject to misalignment, teams can use LLMs to produce structured draft proposals in textual form [47]. These drafts can include multiple variations of mechanics, narrative directions, or system interactions, allowing teams to explore a broader design space early in development. As a result, decision-making becomes more efficient, and teams can converge more quickly on a shared creative vision while still maintaining flexibility for iteration.

In addition, LLMs are effective in generating large volumes of design documentation. These include storyline drafts, quest structures, character backgrounds, dialogue sam-

ples, and detailed descriptions of game systems such as combat mechanics or progression models [19]. Beyond simply accelerating writing, AI tools can help standardize documentation formats, ensure internal consistency across different design elements, and update documents dynamically as changes occur during development. This reduces the manual workload on designers and producers, minimizes the risk of outdated or inconsistent documentation, and improves overall transparency within teams. Consequently, new team members can onboard more quickly, and cross-functional collaboration becomes smoother.

Evidence from software engineering suggests that AI-driven decision-support systems can assist project scheduling, resource allocation, and risk assessment [48]. These capabilities may also be relevant to game production, although direct empirical evidence from game studios remains limited. By identifying patterns in past projects, such as common bottlenecks, task dependencies, or delays associated with specific features, these systems can generate more accurate project timelines and risk assessments. Production managers can use these insights to allocate resources more effectively, anticipate potential issues, and adjust plans proactively rather than reactively. In large-scale productions, this can reduce cost overruns and improve the likelihood of meeting deadlines.

Despite these advantages, the integration of AI into game production also introduces several challenges. Chaudhry argued that the potential over-reliance on automated systems may reduce human oversight and critical evaluation in decision-making processes [49]. Similar risks may arise in game production when AI-generated recommendations are adopted without sufficient human review. While AI can generate plausible suggestions, it may lack contextual understanding of creative goals or team dynamics, leading to suboptimal recommendations if used uncritically. Additionally, the adoption of AI tools requires significant investment in infrastructure, training, and workflow redesign, which may be more accessible to large studios than to smaller developers.

4.3. Programming

In programming, AI contributes to both development and testing, with LLMs playing an increasingly important and multifaceted role throughout the software lifecycle, as shown in Figure 5. Tools based on LLMs, such as Cursor (a code assistant), can generate code snippets, suggest refactoring strategies, and help implement specific functionality from natural language descriptions [50]. Cursor integrates various LLMs like Claude or other code-oriented models, enabling developers to translate high-level design intentions directly into executable code [50,51]. This capability is particularly valuable in game development, where programmers frequently need to implement gameplay logic, scripting systems, physics interactions, or API integrations under tight production timelines. As a result, these tools can reduce development time while also lowering the barrier to experimenting with new ideas.

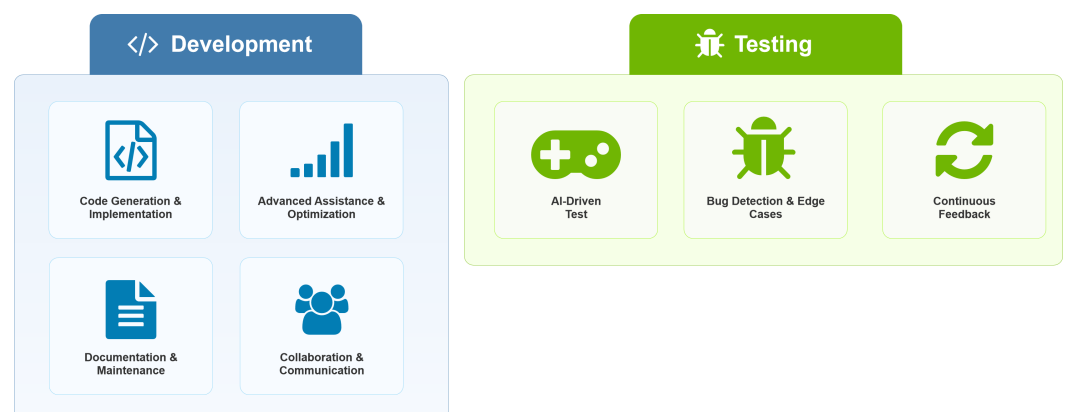


Figure 5. AI (LLMs) in game programming.

Beyond basic code generation, AI-assisted programming tools are increasingly capable of supporting more complex development tasks [52]. They can recommend architectural patterns, identify potential performance bottlenecks, and suggest optimizations tailored to specific game engines or hardware constraints [53]. This is especially useful in performance-critical areas such as real-time rendering, multiplayer synchronization, or memory management. Additionally, programmers can use LLMs interactively to explore alternative implementations in a more conversational way, and can debug issues using similar techniques. These features enhance not only productivity but also the quality of decision-making during development. Evidence from software engineering shows that AI-assisted programming tools can support code generation, refactoring, documentation, debugging, and maintenance. These capabilities are directly relevant to game programming because game development involves comparable software-engineering tasks.

LLMs can also support documentation and code maintenance [54] by automatically generating inline comments, producing technical documentation, explaining legacy code, and summarizing large codebases, which is especially valuable in long-term game projects where multiple developers contribute over extended periods [54]. In complex projects, understanding existing systems can be a major bottleneck, particularly when documentation is incomplete or outdated [55]. AI tools can help mitigate this issue by providing on-demand explanations and maintaining more consistent documentation practices. Furthermore, they facilitate communication between technical and non-technical team members by translating design requirements into implementable code structures, thereby bridging gaps between designers, producers, and engineers.

AI also plays a critical role in quality assurance. Testing, which has traditionally been labor-intensive and time-consuming, can now be partially automated using systems that simulate player behavior and identify bugs more efficiently [5]. These systems can explore a wide range of gameplay scenarios, including rare edge cases that are difficult to anticipate manually. By continuously interacting with the game environment, AI-driven testing tools can uncover issues related to game balance, collision detection, or unexpected system interactions that might otherwise go unnoticed until later stages of development.

Despite these advantages, the integration of AI into programming workflows also introduces several challenges. One concern is the reliability and correctness of AI-generated code, as models may produce syntactically valid but logically flawed solutions [56]. This requires developers to maintain strong oversight and validation practices. Additionally, over-reliance on AI tools may lead to reduced deep understanding of underlying systems, particularly for less experienced programmers [57]. There are also considerations related to code ownership, security, and the use of proprietary or sensitive data when interacting with AI systems.

4.4. Game Operations

Beyond development, AI is also relevant to game operations, particularly in live-service environments that require continuous updates, player interaction, and data-informed decision-making. The evidence identified in this review focuses more on player engagement, personalization, and adaptive game experiences than on game-specific telemetry monitoring or operational anomaly detection, as shown in Figure 6. For example, AI-based approaches have been applied to project coordination and management, including planning, scheduling, and execution support [58], while machine-learning-driven gamification has been explored to improve user engagement and participation [59]. In game development, AI-based approaches have also been applied to personalized content delivery and player retention [60], while deep-learning recommendation systems and reinforcement-learning approaches have been explored for adaptive game content and gameplay [61,62].

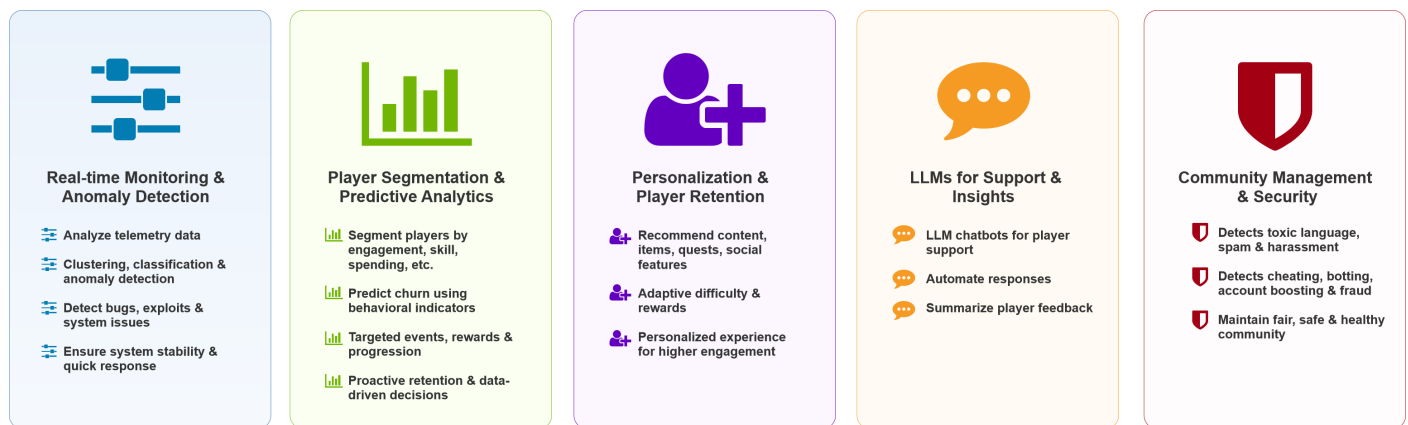


Figure 6. AI in game operations.

Building on this, AI-driven analytics enable more sophisticated player segmentation and behavioral analysis. By grouping players based on engagement patterns, skill levels, or spending behavior, companies can design more targeted operational strategies. For example, different player segments may receive tailored events, rewards, or progression systems that align with their preferences. Predictive models can also be used to forecast player churn by identifying early indicators such as declining activity or changes in playstyle. This allows companies to take proactive measures—such as offering personalized incentives or adjusting gameplay balance—to retain players before disengagement occurs. Such predictive capabilities mark a shift from reactive maintenance to proactive and data-driven game management.

AI also plays a key role in personalization and player (consumer) retention [60]. Recommendation systems, often based on collaborative filtering or deep learning models, can adapt game content, difficulty levels, and in-game offers according to individual player preferences and behavior [61]. For instance, AI can recommend specific quests, cosmetic items, or social features that align with a player's past interactions, thereby enhancing engagement. Reinforcement learning approaches are further used to dynamically adjust gameplay parameters, such as enemy difficulty or reward frequency, creating more engaging and adaptive player experiences [62]. This level of personalization not only improves user satisfaction but also increases the likelihood of long-term retention and monetization.

In addition, LLMs are increasingly used in player-facing and operational support roles. For example, Lee's team developed an LLM-based chatbot to support player learnability in *Stardew Valley* [63]. This study provides game-specific evidence that LLMs can assist players with information and learning during gameplay. However, it does not establish the use of LLMs for customer-service automation, support-ticket resolution, or reductions in operational costs.

AI is also applied in community management and security, which are critical aspects of maintaining a sustainable player ecosystem. Natural language processing techniques can detect toxic language, harassment, or spam in player communications, allowing for automated moderation or real-time intervention. At the same time, machine learning models can identify fraudulent activities such as cheating, account boosting, or bot behavior by analyzing gameplay patterns and anomalies [64]. These systems help maintain a fair and healthy game environment, which is essential for preserving player trust and long-term engagement.

Overall, the evidence reviewed here indicates that AI can support player-facing personalization, adaptive gameplay, recommendation, and player assistance. These applications may contribute to more responsive game services, but the available evidence does not yet establish the extent to which AI automates broader operational functions such as telemetry

monitoring, exploit detection, customer-service ticket resolution, or community management in commercial game studios. These areas therefore remain important directions for further empirical research.

4.5. Comparison

To synthesize the findings across the four occupational areas, Table 1 maps the main AI technologies to the tasks they affect, the occupational groups involved, the type of impact reported, and the nature and strength of the supporting evidence. This comparison shows that the evidence is stronger for task-level changes and productivity enhancement than for occupation-level displacement. It also indicates that evidence for game art, programming, and operations is more directly connected to game-related applications, whereas evidence concerning AI-assisted production management relies more heavily on adjacent software and project-management research.

Table 1. Evidence synthesis of AI impacts across key game development roles.

AI Technology	Task Affected	Occupational Group	Type of Impact	Evidence Type
Generative AI	Concept art, character design, textures, storyboards, and 3D asset creation	Game artists and technical artists	Task transformation; partial automation; productivity enhancement	Game-specific studies and technical/applied studies
LLMs	Concept development, design documentation, communication, and cross-team coordination	Designers, writers, and production managers	Task transformation; productivity enhancement	Game-specific and adjacent software/project-management evidence
AI decision-support systems	Project scheduling, resource allocation, risk assessment, and production planning	Production managers	Task augmentation; productivity enhancement	Adjacent software/project-management evidence; limited direct game evidence
LLMs and AI coding tools	Code generation, refactoring, debugging, documentation, and maintenance	Game programmers	Task transformation; productivity enhancement	Software-engineering studies and game-specific evidence
AI-assisted testing	Automated testing, bug detection, gameplay simulation, and quality assurance	QA testers and programmers	Partial automation; productivity enhancement	Game-related and software-testing evidence
Machine learning	Player segmentation, behavioral analysis, anomaly detection, and telemetry analysis	Game operations and analytics teams	Task augmentation; productivity enhancement	Game-specific empirical and applied studies
Recommendation and reinforcement learning	Personalization, adaptive gameplay, rewards, and player retention	Game designers and operations teams	Task augmentation; service innovation	Game-specific applied studies
LLM-based systems	Customer support, feedback summarization, and community management	Operations and community teams	Task automation; task transformation	Game-related applied evidence and broader AI evidence

5. Career Implications in the Game Industry

The previous section demonstrated how AI is embedded across key stages of game development, from art creation and production management to programming and live operations. These changes provide concrete examples of the three theoretical mechanisms discussed earlier; namely, displacement, task transformation, and productivity effects. Taken together, they suggest that the impact of AI on employment in the game industry is not uniform but instead reflects a complex restructuring of roles, skills, and career trajectories.

From the perspective of displacement, certain tasks within game development are becoming increasingly automated. In game art, generative models can produce large volumes of concept images and textures, reducing the need for manual asset creation in early production stages [6,10]. Similarly, in programming and quality assurance, AI systems can automate code generation, testing, and debugging processes [5,50]. Broader research on AI and employment suggests that entry-level and routine-oriented work may be particularly exposed to automation [65]. Within game development, junior artists and QA testers perform tasks that include asset production and repetitive testing [66,67]. These observations suggest that entry-level game development pathways could face greater automation pressure, although direct longitudinal evidence of reduced entry-level employment in the game industry remains limited. This may raise concerns about career entry and progression for less experienced workers.

However, the evidence from the previous section also strongly supports the task transformation perspective. Rather than eliminating entire occupations, AI tends to reconfigure job content by automating specific tasks while augmenting others. Game artists are increasingly required to guide and refine AI-generated outputs [40], emphasizing skills in artistic direction and tool integration rather than manual production alone [43]. Software-engineering research suggests that AI-assisted programming may shift developers toward reviewing generated code, validating outputs, and handling higher-level design and optimization [53], while similar changes may emerge in game programming, though direct empirical evidence from game studios remains limited. Additionally, production managers rely more on AI-assisted decision-making and data interpretation [47]. These changes suggest that many roles are becoming more hybrid in nature, combining domain expertise with the ability to effectively use AI tools.

This transformation is closely linked to evolving skill requirements. Across all four key areas discussed previously, there is a growing demand for AI literacy, including an understanding of how to interact with models such as diffusion systems or LLMs, how to evaluate their outputs, and how to integrate them into existing workflows. At the same time, traditional skills remain important but are increasingly complemented by higher-level competencies such as critical thinking, creativity, and interdisciplinary collaboration. This shift may advantage workers who are able to adapt quickly, while creating challenges for those whose skills are closely tied to tasks that are more easily automated.

The productivity perspective offers a more optimistic interpretation of these developments. As shown in game production and operations, AI enables faster prototyping, more efficient coordination, and more responsive live services. These improvements can reduce development costs and allow studios to produce more content or expand their services, potentially creating new employment opportunities in areas such as live operations, data analysis, and AI tool development [9]. In addition, studies from adjacent fields, including architecture and engineering, illustrate emerging AI-assisted design and machine-learning integration roles [68,69]. These findings suggest possible directions for new hybrid roles in game development, but direct empirical evidence confirming sustained emergence of such occupations within the game industry remains limited.

Overall, the above evidence indicates that the career implications of AI cannot be adequately characterized as either job displacement or job creation. Across the evidence base, AI appears to affect game development careers through several interconnected mechanisms, including task-level automation, task transformation, skill upgrading, productivity gains, and the emergence of new hybrid roles. Table 2 synthesizes these patterns by linking affected tasks and occupational groups with the underlying AI mechanisms, evidence patterns, and limitations. The synthesis reveals an important distinction between evidence for task-level change and evidence for occupation-level displacement. Evidence for automation and transformation of specific tasks is relatively consistent across game art, programming, quality assurance, and production activities, whereas evidence demonstrating sustained reductions in employment within particular occupations is substantially weaker. Similarly, productivity gains are supported by evidence of faster prototyping, content generation, workflow optimization, and live-service management, though these gains do not necessarily imply net employment growth. Instead, increased productivity may reduce production costs, expand output, or contribute to organizational restructuring depending on market conditions and firm-level strategies.

Table 2. Synthesis of evidence on AI-related career implications in game development.

Career Outcome	Affected Tasks and Roles	AI Mechanism	Evidence Pattern	Key Limitations
Task automation	Routine asset production, quality assurance, and other repetitive tasks; particularly relevant to junior artists and QA roles	Generative AI, automated testing, and other systems that perform standardized or codifiable tasks	Multiple sources indicate that AI can automate or substantially reduce routine components of game development work.	Most evidence concerns task-level automation rather than observed reductions in occupational employment.
Task transformation	Artists, programmers, designers, and production managers	AI-assisted generation, code assistance, decision support, and workflow automation	Evidence consistently indicates a shift from manual execution toward reviewing, refining, supervising, and integrating AI outputs.	Direct empirical evidence from game studios remains limited for some occupations, particularly programming and management.
Skill upgrading	Artists, programmers, designers, technical artists, and production staff	Integration of generative AI, LLMs, machine learning, and AI-enabled production tools	Multiple sources indicate growing importance of AI literacy, critical evaluation, creative direction, and interdisciplinary skills.	The precise skill requirements vary across roles and studios, and longitudinal evidence remains limited.
Productivity and output expansion	Development, production, live operations, marketing, and support functions	Faster prototyping, content generation, workflow optimization, personalization, and analytics	Evidence suggests that AI can reduce development time and support increased content production and more responsive live services.	Productivity gains do not necessarily translate into additional employment and may instead contribute to cost reduction or market concentration.

Table 2. *Cont.*

Career Outcome	Affected Tasks and Roles	AI Mechanism	Evidence Pattern	Key Limitations
Emerging occupations and opportunities	AI-assisted designers, technical artists, AI pipeline specialists, data analysts, and ML/ AI integration roles	Creation of new AI-enabled workflows and products	Emerging evidence identifies new hybrid roles and new areas of technical and creative expertise.	Most evidence is recent and descriptive; sustained employment growth has not yet been established longitudinally.
Occupational displacement	Potentially exposed routine and entry-level positions	Substitution of codifiable tasks by AI systems	Theoretical and cross-sector evidence suggests greater exposure for routine and entry-level work, with some game-specific evidence of task automation.	Direct longitudinal evidence demonstrating sustained reductions in game-industry employment is limited.

6. Challenges and Opportunities of AI Adoption

While the previous section has examined how AI reshapes careers within the game industry, a broader perspective reveals that its adoption also introduces a set of challenges and opportunities across multiple stakeholders. These effects extend beyond individual firms and workers, influencing societal structures, industry competition, and the future workforce pipeline. Understanding these dimensions is essential for evaluating the long-term implications of AI-driven transformation.

6.1. Society

From a societal perspective, the adoption of AI in the game industry reflects broader transformations occurring across the digital economy, where automation, machine learning, and intelligent systems are increasingly reshaping labor markets, game creative industries, and patterns of cultural production. While the integration of AI into workflows has the potential to improve efficiency and reduce development costs, it also introduces significant social and economic challenges. One concern identified in the literature is employment polarization [70,71]—as routine, repetitive, and entry-level tasks become increasingly automated, opportunities for inexperienced workers may diminish, potentially exacerbating income inequality and reducing pathways for upward mobility within the industry [70]. Research on AI and creative industries suggests that these effects may be particularly important for smaller organizations with fewer resources for technological adoption and workforce adaptation [71]; similar implications may apply to small- and medium-sized game studios, although direct comparative evidence remains limited. Reductions in these positions could make it more difficult for aspiring developers to gain practical experience and establish long-term careers in the sector.

At the same time, AI adoption also creates opportunities for wider participation in game development and digital content creation. Generative AI tools lower technical and financial barriers, enabling individuals with limited formal training or smaller budgets to produce game assets, prototypes, narratives, or even complete interactive experiences [10]. Independent developers and hobbyists can now access capabilities that were previously limited to large studios with specialized teams. This democratization of production may

contribute to a more diverse range of creative voices, cultural perspectives, and experimental ideas within the industry, potentially fostering greater innovation and inclusivity. Furthermore, AI-assisted tools may support accessibility by helping creators overcome language, artistic, or technical limitations. However, these benefits are accompanied by important ethical and legal concerns. Questions surrounding intellectual property ownership, authorship, transparency, and the ethical use of copyrighted training data remain unresolved and continue to generate debate among developers, policymakers, and researchers [72]. Addressing these concerns will likely require clearer regulatory frameworks and stronger institutional oversight.

In addition, there are growing concerns regarding the long-term societal consequences of increasing dependence on AI systems in game creative industries. As more creative and technical processes become mediated or partially automated by AI, there is a risk of homogenization in artistic output and a decline in human-driven originality [73,74]. AI models often generate content based on patterns learned from existing works, which may encourage repetitive design conventions and reinforce dominant aesthetic trends [74]. Over-reliance on such systems could gradually reduce experimentation and weaken the distinct creative identities of individual studios or creators. There are also concerns that excessive automation may diminish opportunities for skill development, as developers become more dependent on AI-generated solutions rather than cultivating their own technical or artistic expertise. Balancing the productivity and efficiency gains offered by AI with the preservation of human creativity, cultural diversity, and meaningful artistic expression therefore remains one of the central societal challenges facing the future of the game industry.

6.2. Game Companies

For game companies, the adoption of AI presents both significant strategic opportunities and substantial operational challenges. On the opportunity side, AI technologies can improve productivity across multiple stages of the development pipeline by accelerating production cycles, reducing operational costs, and enabling more data-driven decision-making processes [6]. Studios can iterate more rapidly on game concepts, automate repetitive production tasks, and optimize workflows in areas such as asset creation, quality assurance, localization, and customer support. AI systems can also support more personalized player experiences by analyzing player behavior and dynamically adapting gameplay, recommendations, or monetization strategies [20]. In live-service games, AI-driven analytics allow companies to monitor player engagement in real time, predict churn, and respond more effectively to community trends [75]. These capabilities can strengthen player retention, improve service responsiveness, and create new revenue opportunities, particularly in areas such as live operations, procedural content generation, and user-generated content ecosystems.

However, the benefits of AI adoption are not distributed evenly across the industry. Evidence from the wider creative industry suggests that larger organizations may be better positioned to absorb the costs of AI infrastructure, specialized expertise, and organizational adaptation⁶⁹. In the game industry, this may translate into advantages for large studios and publishers, although direct comparative evidence remains limited [71]. These findings provide a basis for considering resource differences among game companies, but direct comparative evidence on AI adoption between large studios, publishers, and independent developers remains limited. Smaller studios and independent developers, by contrast, may face difficulties affording these technologies or competing for highly skilled workers [71]. These resource differences may provide advantages to established companies and could contribute to a widening gap between major publishers and smaller market participants.

If such differences persist, industry concentration could potentially increase, although direct evidence of this effect in the game industry remains limited. It may potentially reduce marketplace diversity and make it more difficult for new entrants to compete effectively. The growing reliance on proprietary AI ecosystems may also increase dependence on large technology providers, further consolidating power within the industry.

There are also significant organizational and managerial challenges associated with integrating AI into existing development workflows. Companies must invest in reskilling and upskilling their workforce to ensure that employees can effectively collaborate with AI-assisted systems [76]. This may involve redesigning production pipelines, redefining job responsibilities, and creating new interdisciplinary roles that combine technical, creative, and analytical expertise. Resistance to organizational change may emerge if employees perceive AI as a threat to job security or professional identity. Furthermore, firms must manage the risks associated with AI-generated outputs, including inconsistent quality, embedded bias, misinformation, and potential legal or copyright violations [76]. Ensuring transparency, accountability, and compliance with evolving regulations adds additional complexity to AI governance within studios.

Another important concern is the potential over-reliance on AI systems in creative decision-making. Excessive dependence on automated tools may reduce human oversight and weaken creative experimentation, potentially affecting the originality, artistic identity, and overall quality of games [77]. AI-generated assets and narratives may prioritize efficiency and pattern replication over innovation, leading to more formulaic content if developers rely too heavily on algorithmic outputs. Companies therefore face the challenge of balancing automation-driven efficiency gains with the preservation of human creativity, collaboration, and design vision. Successfully navigating this balance will likely become a critical factor in determining the long-term sustainability and cultural impact of AI adoption within the game industry.

6.3. Employees

For current employees, AI adoption may alter aspects of work within the game industry. Broader research on AI and human-capital obsolescence suggests that workers whose skills are closely tied to tasks affected by automation may face greater pressure to adapt [18]. Within the game industry, repetitive asset production, quality assurance, localization, and basic scripting can be considered relevant areas for examining potential task-level changes, but the available evidence does not establish that these occupations are uniformly more vulnerable to automation. Workers whose responsibilities are heavily task-based, repetitive, or routine-oriented may find increasing portions of their jobs automated through AI-assisted systems and generative technologies. Roles involving repetitive asset production, quality assurance testing, localization, or basic scripting are particularly vulnerable to partial automation. As AI systems become more capable, employees may be required to adapt continuously by acquiring new technical, analytical, and collaborative competencies [18]. This transition can be especially difficult for workers with limited access to training opportunities or those who have become highly specialized in traditional workflows that are gradually losing relevance. Older workers or employees in smaller studios may face additional barriers due to limited organizational support, financial constraints, or reduced exposure to emerging technologies.

At the same time, AI adoption also creates opportunities for career advancement, professional growth, and role evolution. Employees who develop AI literacy and the ability to collaborate effectively with intelligent systems may transition into higher-value responsibilities such as innovation management, system supervision, creative direction, and strategic decision-making [78]. Rather than simply replacing human labor, AI can

augment human capabilities by automating repetitive processes and allowing workers to focus on more complex, creative, and meaningful aspects of game development. Developers may spend less time on repetitive implementation tasks and more time refining gameplay experiences, narrative design, or player engagement strategies. Similarly, artists and designers can use generative tools to accelerate experimentation and explore a wider range of creative possibilities. Employees who successfully integrate AI into their workflows may therefore increase both their productivity and their long-term employability.

For recent graduates and students entering the workforce, the challenges associated with AI adoption are somewhat different. The potential automation of entry-level and routine-oriented tasks may make it more difficult for newcomers to gain practical industry experience, potentially increasing barriers to entry [70]. Fierro expressed concern that traditional career pathways, in which workers begin in junior roles and gradually progress through hands-on learning and mentorship, may become less accessible as automation could reduce the availability of some of these positions [70]. Internships and junior production roles have historically played an important role in helping graduates develop industry knowledge, professional networks, and technical confidence. If these opportunities decline, aspiring developers may struggle to establish themselves within the industry, particularly those from less privileged educational or socioeconomic backgrounds.

However, new opportunities are also emerging for this group as educational institutions increasingly incorporate AI-related competencies into their curricula [79]. Universities and training programs are beginning to emphasize AI literacy, computational creativity, data analysis, and interdisciplinary collaboration as essential skills for future professionals [79]. As a result, graduates may enter the workforce with capabilities that align more closely with evolving industry demands. Students who are proficient in AI-assisted workflows, adaptive learning, and emerging development technologies may be particularly well positioned to secure roles in areas such as AI-assisted design, technical art, procedural content generation, and machine learning integration [80]. In this sense, while AI may disrupt traditional employment pathways, it also encourages the development of new forms of expertise and may ultimately reshape how future generations prepare for careers in the game industry.

In summary, the adoption of AI in the game industry generates a complex set of trade-offs across society, companies, and workers. While it offers significant potential for innovation, efficiency, and new forms of participation, it also introduces risks related to inequality, market concentration, and workforce disruption. Addressing these challenges requires coordinated efforts from industry leaders, policymakers, and educational institutions to ensure that the benefits of AI are broadly shared and that its negative impacts are effectively mitigated.

7. Conclusions

In this study, we examined the role of AI in the game industry, focusing on its implications for development workflows, employment, and broader industry dynamics. By drawing on the three complementary perspectives of displacement, task transformation, and productivity effects, our analysis provides a broad understanding of how AI reshapes both work and value creation in this domain.

The reviewed literature indicates that AI has been increasingly integrated into multiple stages of the game development lifecycle, including concept art, narrative design, programming, production management, and live operations. The evidence suggests potential gains in efficiency, prototyping, content generation, and data-driven decision-making, although the extent of adoption varies across roles and studios. These findings are broadly consistent with previous reviews: Amankwah-Amoah discussed the opportunities and

challenges of generative AI across creative industries [18], while Stige examined AI applications in UX design [19] and Lao reviewed AI-driven game design and user experience research [20]. Consistent with these studies, the present review identifies important applications of AI in creative production, design, and user-facing game experiences.

The contribution of this review is not to claim that these effects of AI are entirely new; rather, it brings together evidence concerning AI applications across the wider game development lifecycle and connects this evidence with questions concerning work practices, skills, productivity, and career implications. This broader perspective helps distinguish technical capabilities and task-level changes from direct evidence concerning employment outcomes.

At the same time, the impact of AI on employment is complex and uneven. The displacement perspective suggests that routine and entry-level tasks may face greater automation pressure, particularly in areas such as asset creation and quality assurance. The task transformation perspective suggests that AI may reconfigure many roles by automating some tasks while increasing the importance of human–AI collaboration, supervision, and integration. Meanwhile, the productivity perspective points to new opportunities for innovation, including the emergence of hybrid roles and the expansion of game content and services. Together, these findings suggest that AI is currently associated more clearly with changes in tasks and work practices than with demonstrated large-scale occupational replacement in the game industry.

Our study also identifies several critical challenges associated with AI adoption, including ethical and legal concerns related to intellectual property and training data, risks of deskilling and task fragmentation, and unequal access to AI technologies across firms and workers. In particular, the possibility of changes to entry-level roles raises important questions about career pathways and long-term workforce sustainability. At the industry level, the uneven distribution of AI capabilities may contribute to increased market concentration, limiting the broader benefits of technological progress. Beyond employment and productivity, AI adoption requires ethical and legal governance concerning copyright, authorship, transparency, and training data. Game studios should maintain human involvement in creative decisions and support creative diversity. Smaller studios may also need accessible AI tools, shared infrastructure, training, and policy support to reduce adoption costs and avoid market concentration and creative homogenization.

Despite these challenges, AI may create opportunities for productivity improvement, creative experimentation, and new forms of game content and player experience. Similarly, AI may reduce production costs, support smaller development teams, and enable new forms of content and player experience. These potential benefits do not necessarily translate into net employment growth or equal benefits for all firms and workers. At the same time, advancements in personalization, procedural generation, and adaptive gameplay open new possibilities for player engagement and experience design. These developments suggest that AI can serve not only as a tool for efficiency but also as a driver of innovation in the industry.

Overall, our review finds that the strongest current evidence concerns AI capabilities, workflow changes, and task-level transformation. Evidence concerning actual employment outcomes, occupational displacement, market concentration, and long-term career development remains limited and uneven. Maximizing the benefits of AI while mitigating its risks requires continuous skill development, organizational adaptation, and appropriate regulatory frameworks. Future research could further explore empirical evidence on employment outcomes, differences across regional markets, and the long-term implications of AI-driven production models. As AI technologies continue to evolve, their influence on the game industry will remain a key area for both academic inquiry and practical consideration.

Limitations and Future Research

A key limitation of this review is the scarcity of direct empirical evidence on employment outcomes in the game industry. The reviewed literature provides stronger evidence of AI capabilities, workflow changes, and task-level transformation than of actual changes in employment levels, occupational displacement, or career progression. Therefore, claims concerning employment polarization, reduced entry-level opportunities, and occupational restructuring should be interpreted as potential implications rather than established industry-wide outcomes.

Several methodological limitations should also be considered. First, the review was restricted to English-language publications, which may have excluded relevant evidence published in other languages. Second, the evidence base was heterogeneous in terms of AI definitions, research designs, and source types. Industry and vendor reports were useful for identifying emerging practices and industry developments, but their findings may be subject to organizational or commercial interests and should not be considered equivalent to independent empirical evidence. Third, publication and database/search-term bias may have affected the evidence identified by the review, despite the use of multiple databases and backward and forward citation tracking. Finally, the rapid development of AI models and capabilities means that some findings may become outdated as technologies and industry practices continue to evolve.

Future research should move beyond AI capabilities and workflow changes to examine actual employment outcomes in game development. Longitudinal studies could track employment levels, occupational mobility, and career progression over time, while occupational task analyses, surveys of game development professionals, and studio-level adoption studies could provide more direct evidence of how AI affects different roles. Comparative research across company sizes and regions would also help identify how organizational resources, labor markets, and adoption strategies shape these outcomes.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/computers15100693/s1>. Table S1: PRISMA 2020 Checklist

Author Contributions: Conceptualization, Y.X. and G.F.; Methodology, Y.X. and G.F.; Investigation, Y.X.; Resources, H.Y., S.Y., C.F., T.H. and J.S.; Writing—original draft preparation, Y.X., S.Y., C.F., T.H., J.S., H.Y., K.C. and G.F. All authors have read and agreed to the published version of the manuscript.

Funding: This work was partly supported by 2025 Guangdong Education Science Planning Project (Higher Education Project) (Grant no. 2025GXJK0510), and Guangzhou Education Bureau (Grant Number: 2023KCSZ036).

Institutional Review Board Statement: Ethical approval was not required as no human participants were involved in this research.

Informed Consent Statement: Informed consent was not required as no human participants were involved in this research.

Data Availability Statement: No new data were created or analyzed in this study. The database-specific search strategies, including search dates, search fields, complete search strings, applied filters, and numbers of records retrieved, are provided in Table A1 in Appendix A. The screening and study selection process, including exclusions at each stage, is reported in Figure 1. The evidence corpus and extracted information used for the thematic synthesis are provided in Table A2 in Appendix A.

Acknowledgments: During the preparation of this manuscript /study, the author(s) used ChatGPT (OpenAI, GPT-5 mini) and Writefull (V1.0.6.0) for the purposes of proofreading. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Database-specific search strategies, search fields, filters, and results.

Database	Search Date	Search Fields	Complete Search String	Filters/Limits	Results
Google Scholar	[01/06/2026–15/06/2026]	Google Scholar search field	("artificial intelligence" OR "generative AI" OR "machine learning" OR "procedural content generation" OR AI) AND ("game development" OR "game industry" OR "game design" OR "games" OR "creative industries") AND ("employment" OR "career" OR "skills" OR "workforce" OR "jobs" OR "automation" OR "workflow" OR "asset creation" OR "game programming" OR "game operation" OR "content pipeline" OR "level design" OR "creative work")	English; 2020–2026	52
Scopus	[01/06/2026–05/06/2026]	TITLE-ABS-KEY	("artificial intelligence" OR "generative AI" OR "machine learning" OR "procedural content generation" OR AI) AND ("game development" OR "game industry" OR "video game" OR "games" OR "game design" OR "creative industries") AND ("employment" OR "career" OR "skill" OR "workforce" OR "labor" OR "labour" OR "job" OR "occupation" OR "automation" OR "workflow" OR "asset creation" OR "game programming" OR "game operation" OR "content pipeline" OR "level design" OR "creative work")	English; 2020–2026; articles and conference papers	48
IEEE Xplore	[06/06/2026–10/06/2026]	TITLE-ABS	("artificial intelligence" OR "generative AI" OR "machine learning" OR "procedural content generation" OR AI) AND ("game development" OR "game industry" OR "video game" OR "games" OR "game design" OR "creative industries") AND ("employment" OR "career" OR "skill" OR "workforce" OR "labor" OR "labour" OR "job" OR "occupation" OR "automation" OR "workflow" OR "asset creation" OR "game programming" OR "game operation" OR "content pipeline" OR "level design" OR "creative work")	English; 2020–2026; journals and conference publications	39
Web of Science Core Collection	[03/06/2026–12/06/2026]	TS	("artificial intelligence" OR "generative AI" OR "machine learning" OR "procedural content generation" OR AI) AND ("game development" OR "game industry" OR "video game" OR "games" OR "game design" OR "creative industries") AND ("employment" OR "career" OR "skill" OR "workforce" OR "labor" OR "labour" OR "job" OR "occupation" OR "automation" OR "workflow" OR "asset creation" OR "game programming" OR "game operation" OR "content pipeline" OR "level design" OR "creative work")	English; 2020–2026; articles and proceedings papers	35

Table A2. Evidence corpus and data extraction table.

Item	Year	Evidence Category	Methodology	Key Findings	Reported Implications
1 [2]	2023	Contextual source	Conceptual essay/position piece	Highlights the promise and peril of human-like AI for work and creativity.	Use human-centered AI design and avoid over-automation.
2 [1]	2021	Evidence source (Adjacent domain/ Extrapolative)	Conference conceptual study	Links AI with innovation-management transformation.	Adapt innovation processes and managerial skills to AI.
3 [3]	2024	Evidence source	Conceptual review/research agenda	Predicts generative AI will disrupt creative industries.	Invest in reskilling, governance, and new creative workflows.
4 [15]	2022	Contextual source	Industry/geography analysis	Shows Tencent’s platform power in mobile gaming production networks.	Platform concentration shapes labor, suppliers, and market access.
5 [4]	2021	Evidence source (Adjacent domain/ Extrapolative)	Conceptual review	Presents an automation–augmentation paradox in management.	Managers should combine automation with augmentation-oriented design.
6 [7]	2022	Evidence source	Survey	Reviews procedural content generation methods for games.	PCG can speed development and expand design possibilities.
7 [8]	2024	Evidence source	Applied analytics/case study	Uses AI to analyze game tactics and player performance.	AI can support coaching, balancing, and decision-making in games.
8 [5]	2024	Evidence source	Conceptual/design-oriented article	Frames game development as AI-driven collaborative co-creation.	Teams can use AI as a creative partner in production.
9 [9]	2025	Evidence source	Perspective/conceptual article	Argues AI is creating new job roles and career pathways.	Workforce planning should focus on emerging AI roles.
10 [6]	2024	Evidence source	HCI system study	Supports character design and illustration prototyping with generative AI.	Generative AI can accelerate early concepting for artists.
11 [17]	2026	Evidence source	Legal analysis	Examines copyright boundaries for AI-generated content in game development.	Studios need compliance strategies for AI-authored assets.
12 [10]	2025	Evidence source	Post-gamejam user study	Evaluates generative AI in game asset creation.	AI can help indie teams prototype faster but needs oversight.
13 [12]	2024	Evidence source	Field commentary/conceptual review	Raises open questions about generative AI in illustration.	Illustrators need clearer norms around authorship and value.
14 [11]	2025	Evidence source	Experimental/systems study	Shows generative AI agents can automate QA testing.	QA work may shift toward supervision and exception handling.
15 [24]	2003	Foundational literature	Empirical labor-economics study	Documents skill-biased technological change in labor demand.	Technology raises demand for cognitive/analytic skills.

Table A2. *Cont.*

Item	Year	Evidence Category	Methodology	Key Findings	Reported Implications
16 [25]	2017	Foundational literature	Task-based labor risk analysis	Estimates many jobs are susceptible to computerization.	Policymakers should plan for displacement and retraining.
17 [26]	2022	Foundational literature	Conceptual framework	Defines cognitive automation for knowledge work.	Organizations should redesign tasks around human–machine collaboration.
18 [27]	2022	Evidence source (Adjacent domain/ Extrapolative)	Applied review/ discussion	Links ML/ AI with work-performance and employee behavior optimization.	AI can improve productivity, but monitoring and ethics matter.
19 [31]	2013	Foundational literature	Conceptual review	Explains the task approach to labor markets.	Task redesign matters more than occupation labels.
20 [32]	2024	Evidence source (Adjacent domain/ Extrapolative)	Conceptual essay	Argues AI causes job shifting rather than outright job loss.	Workers should transition to complementarity-based roles.
21 [35]	2026	Contextual source (Adjacent domain/ Extrapolative)	Firm-level empirical report	Studies AI adoption, productivity, and employment in European firms.	AI uptake appears tied to productivity gains and labor reallocation.
22 [36]	2026	Contextual source (Adjacent domain/ Extrapolative)	Firm-data report	Compiles firm-level evidence on AI adoption.	Better measurement is needed to track AI’s labor market effects.
23 [19]	2024	Evidence source	Systematic literature review	Reviews AI for UX design.	AI can support ideation, but UX quality and control remain central.
24 [37]	2025	Evidence source	Applied article	Argues AI and art styles can maximize game development efficiency.	AI may speed asset pipelines while preserving creative expression.
25 [14]	2025	Evidence source	Book chapter/ review	Explores generative AI for immersive gaming experiences.	Generative AI can deepen personalization and immersion.
26 [58]	2024	Evidence source	Technical report/ framework	Presents AI-powered project management for group coordination.	AI can improve planning, scheduling, and execution.
27 [59]	2023	Evidence source	Applied study	Applies machine learning-driven gamification to engagement.	Personalization can raise user retention and participation.
28 [16]	2025	Contextual source	Industry market report	Analyzes China’s games market structure and trends.	Market concentration and regulation shape employment and production opportunities.
29 [13]	2024	Evidence source	HCI/design study	Explores generative AI support for indie game development.	Indie developers may gain a co-worker-like assistant but need control.
30 [22]	2020	Methodological reference	Methodological review	Compares academic search systems for systematic reviews.	Improves evidence retrieval quality for AI/employment reviews.

Table A2. Cont.

Item	Year	Evidence Category	Methodology	Key Findings	Reported Implications
31 [21]	2017	Methodological reference	Methods paper	Evaluates Boolean search-string efficiency for information retrieval.	Stronger search methods improve literature review rigor.
32 [23]	2019	Foundational literature	Theoretical/empirical economics review	Explains how automation can displace and create tasks.	Policy should support task creation and worker transitions.
33 [30]	2020	Foundational literature	Conference paper	Unpacks skill bias via automation and new tasks.	Automation changes task composition, not just headcount.
34 [33]	2026	Evidence source (Adjacent domain/ Extrapolative)	Theoretical/empirical management study	Examines AI roles in human collaboration: automation and augmentation.	Organizations should allocate tasks by human and AI comparative advantage.
35 [34]	2019	Evidence source (Adjacent domain/ Extrapolative)	Empirical economics study	Finds automation can boost employment in some contexts.	Complementary demand and productivity growth can offset displacement.
36 [38]	2018	Evidence source (Adjacent domain/ Extrapolative)	NBER report	Analyzes whether automation is labor-displacing.	Employment effects depend on productivity, demand, and labor share.
37 [39]	2021	Evidence source (Adjacent domain/ Extrapolative)	Empirical economics study	Shows search complementarities can amplify concentration and monopsony.	AI/search systems may intensify labor market concentration.
38 [40]	2025	Evidence source	HCI/system study	Improves controllability of image refinement in environment design via traceable prompts.	Prompt traceability can help creators manage AI outputs.
39 [41]	2025	Evidence source	Technical preprint	Presents high-fidelity generative texturing for 3D shapes.	Generative tools can accelerate 3D asset production.
40 [42]	2024	Evidence source	Computer-vision methods paper	Uses 2D visual prompts for text-to-3D generation.	Prompt-based 3D generation may reduce manual modeling work.
41 [43]	2026	Evidence source	Comparative evaluation	Compares text-to-3D AI tools for urban furniture design.	Tool choice affects fidelity, usability, and design workflow.
42 [44]	2025	Evidence source	Comparative study	Compares DeepMotion and Autodesk Maya for animation creation/learning.	AI tools can improve speed, but conventional tools remain important for learning.
43 [45]	2024	Evidence source	Case study/evaluation	Assesses accuracy of cloud-based 3D pose-estimation tools.	AI pose tools can assist production, but accuracy limits matter.
44 [47]	2025	Evidence source	Exploratory study	Explores LLM use in digital game development.	LLMs can support coding, ideation, and documentation in games.
45 [48]	2025	Evidence source (Adjacent domain/ Extrapolative)	Systems/applied study	Applies AI decision support to agile project management.	AI can aid risk mitigation and resource allocation.

Table A2. Cont.

Item	Year	Evidence Category	Methodology	Key Findings	Reported Implications
46 [46]	2025	Contextual source	Comparative evaluation	Compares ChatGPT and Gemini as scientific writing assistants.	AI writing tools vary in quality, so oversight is needed.
47 [51]	2026	Contextual source	Product/platform description	Presents Claude as an AI LLM platform.	LLMs may reshape software workflows.
48 [54]	2025	Evidence source (Adjacent domain/ Extrapolative)	Dataset paper	Introduces code-documentation alignment data for maintenance.	Better benchmarks can improve maintenance tooling and training.
49 [60]	2024	Evidence source	Applied study	Applies AI to personalized content delivery and retention.	Personalization can increase engagement and loyalty.
50 [61]	2025	Evidence source	Technical conference paper	Proposes personalized game-content recommendation with deep learning.	Adaptive recommendation can improve player experience.
51 [62]	2024	Evidence source	Survey	Reviews machine learning techniques for adaptive game design.	AI can enable dynamic difficulty and personalization.
52 [63]	2025	Evidence source	Diary study/HCI evaluation	Develops an LLM chatbot to support learnability in <i>Stardew Valley</i> .	LLM assistants can lower learning barriers for players.
53 [64]	2025	Evidence source	Literature review	Reviews NLP methods for textual cyber-abuse detection.	LLMs can support moderation and harm detection.
54 [49]	2024	Evidence source	Conceptual article	Discusses balancing AI automation and human oversight in governance.	Decision systems should preserve accountability.
55 [57]	2025	Evidence source	Empirical education study	Examines how AI tools influence young developers' skills.	AI can speed coding, but may change skill development patterns.
56 [56]	2025	Evidence source	Conference experiment	Tests accuracy of AI-generated code and its productivity effects.	Productivity gains depend on code correctness and review.
57 [50]	2026	Contextual source	Product/platform description	Presents Cursor as an AI coding platform.	AI-native editors may reshape software workflows.
58 [52]	2024	Evidence source (Adjacent domain/ Extrapolative)	Applied programming study	Uses code embeddings and transformers for programming tasks.	AI can support code understanding and generation.
59 [53]	2025	Evidence source (Adjacent domain/ Extrapolative)	Applied methods article	Studies AI-based algorithm design and optimization in programming.	AI can help automate optimization and solution search.
60 [55]	2022	Evidence source (Adjacent domain/ Extrapolative)	Survey/practice paper	Reviews documentation approaches in continuous software development.	Documentation remains essential as AI speeds code change.
61 [65]	2025	Contextual source	Book	Argues entry-level jobs are collapsing under autonomous AI agents.	Workforce systems need new entry pathways and training.

Table A2. Cont.

Item	Year	Evidence Category	Methodology	Key Findings	Reported Implications
62 [67]	2024	Evidence source	Applied article	Shows AI is redefining QA from test design to data generation.	QA roles may shift toward supervision and strategy.
63 [66]	2025	Evidence source	Conceptual/empirical article	Asks whether generative AI enhances creativity or constrains innovation in game design.	Creative gains may be offset by homogenization risks.
64 [68]	2024	Evidence source (Adjacent domain/Extrapolative)	Empirical study	Studies AI design assistance in novice architectural design.	AI can support novices but may affect learning and independence.
65 [69]	2022	Evidence source (Adjacent domain/Extrapolative)	Review	Integrates scientific knowledge with machine learning for engineering systems.	Hybrid human–ML workflows can improve complex decision-making.
66 [71]	2024	Evidence source	Conceptual article	Discusses continuity versus discontinuity of work in creative industries.	AI may reconfigure creative labor rather than simply replace it.
67 [70]	2022	Evidence source (Adjacent domain/Extrapolative)	Economic model/empirical study	Analyzes automation, job polarization, and structural change.	Automation can widen polarization across skill groups.
68 [72]	2025	Evidence source (Adjacent domain/Extrapolative)	Policy review	Reviews governance issues in generative AI.	Governance frameworks are needed for safe and fair deployment.
69 [73]	2026	Evidence source	Conceptual article	Warns AI can make content more similar.	Organizations should balance efficiency with diversity and originality.
70 [74]	2024	Evidence source	Experimental study	Finds LLMs can homogenize human creative ideation.	Teams should preserve diverse prompts and human critique.
71 [20]	2025	Evidence source	Systematic review	Reviews AI-driven game design and UX research.	AI offers design support, but evidence on UX impact remains uneven.
72 [76]	2025	Evidence source (Adjacent domain/Extrapolative)	Review	Reframes work, skills, and education for the AI economy.	Education and reskilling are central to transition management.
73 [77]	2026	Evidence source	Conceptual chapter	Discusses the paradox of AI and creativity.	AI can both enhance and hinder innovation depending on use.
74 [18]	2025	Evidence source (Adjacent domain/Extrapolative)	Conceptual/review article	Links AI-induced human capital obsolescence to business failure.	Firms should invest in capability renewal and adaptation.
75 [78]	2025	Evidence source (Adjacent domain/Extrapolative)	Conference paper	Explores AI’s effects on work environment and decision-making.	AI can improve decisions but may increase dependence on systems.
76 [79]	2025	Contextual source (Adjacent domain/Extrapolative)	Empirical education study	Examines AI’s impact on curriculum development in higher education.	Curricula should adapt to AI-related skills and ethics.
77 [80]	2025	Contextual source (Adjacent domain/Extrapolative)	Book chapter	Discusses AI-assisted technologies in education.	AI can personalize learning and support instruction.

Table A2. Cont.

Item	Year	Evidence Category	Methodology	Key Findings	Reported Implications
78 [75]	2022	Evidence source	Applied model	Proposes digital innovation for competitive gaming engagement and UX.	Innovation can improve engagement and player experience.
79 [28]	2015	Foundational literature	Policy report	Examines creativity vs robots in the creative economy.	Creative work needs support as automation expands.
80 [29]	2015	Foundational literature	Handbook chapter	Defines and surveys creative industries.	Creative-industry analysis helps frame AI, labor, and value creation.

Table A3. List of documents not from 2020 to 2026.

Item	Title	Year	Key Views	Reason on List
1	The skill content of recent technological change: An empirical exploration [24]	2003	Technological change substitutes for routine tasks while increasing demand for non-routine analytical and interactive skills.	Foundational labor market theory
2	The “task approach” to labor markets: an overview [31]	2013	Argues that labor market outcomes are better understood through the tasks workers perform rather than occupations alone, because technology reshapes task demand unevenly.	Foundational labor market theory
3	Creativity vs robots: The creative economy and the future of employment [28]	2015	Concludes that creative occupations are generally less susceptible to automation because they rely heavily on originality and complex social intelligence.	Perspective
4	Creative industries [29]	2015	Describes creative industries as sectors driven by symbolic knowledge, project-based work, and the production of cultural and economic value, and hard to be replaced by automation.	Perspective
5	The future of employment: How susceptible are jobs to computerisation? [25]	2017	Estimates that a substantial share of jobs are at high risk of computerisation, particularly occupations involving routine and predictable tasks.	Perspective
6	Efficiency of Boolean search strings for Information retrieval? [21]	2017	Evaluates Boolean search-string efficiency for information retrieval.	Search methods

Table A3. Cont.

Item	Title	Year	Key Views	Reason on List
7	Is automation labor-displacing? Productivity growth, employment, and the labor share [38]	2018	Shows that, while automation can reduce employment in directly affected industries, productivity gains also generate broader employment growth through new demand and tasks.	Foundational labor market theory
8	Automation and jobs: When technology boosts employment [34]	2019	Finds automation can boost employment in some contexts.	Perspective
9	Automation and new tasks: How technology displaces and reinstates labor [23]	2019	Shows that automation can displace labor from existing tasks, while the creation of new tasks can reinstate labor demand.	Perspective

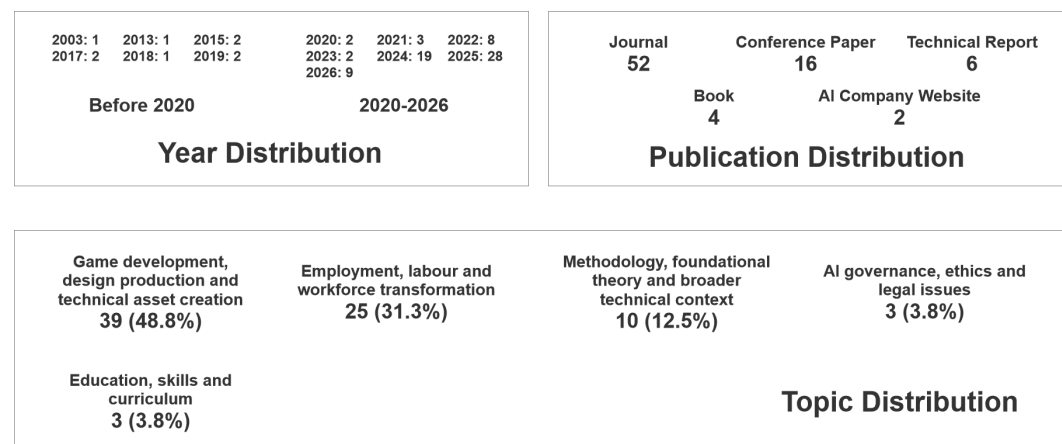


Figure A1. Year, publication, and topic distribution of sources.

References

- Correia, M.J.; Matos, F. The impact of artificial intelligence on innovation management: A. In *Proceedings of the ECIE 2021 16th European Conference on Innovation and Entrepreneurship*; Academic Conferences Limited: Reading, UK, 2021; Volume 1, pp. 222–230.
- Brynjolfsson, E. The turing trap: The promise & peril of human-like artificial intelligence. In *Augmented Education in the Global Age*; Routledge: Abingdon, UK, 2023; pp. 103–116.
- Amankwah-Amoah, J.; Abdalla, S.; Mogaji, E.; Elbanna, A.; Dwivedi, Y.K. The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *Int. J. Inf. Manag.* **2024**, *79*, 102759.
- Raisch, S.; Krakowski, S. Artificial intelligence and management: The automation–augmentation paradox. *Acad. Manag. Rev.* **2021**, *46*, 192–210.
- Ratican, J.; Hutson, J. Video game development 3.0: AI-driven collaborative co-creation. *Metaverse* **2024**, *5*, 2904. <https://doi.org/10.54517/m2904>.
- Ling, L.; Chen, X.; Wen, R.; Li, T.J.-J.; Ray, L. Sketchar: Supporting character design and illustration prototyping using generative AI. *Proc. ACM Hum. Comput. Interact.* **2024**, *8*, 1–28.
- Zhang, Y.; Zhang, G.; Huang, X. A survey of procedural content generation for games. In *2022 International Conference on Culture-Oriented Science and Technology (CoST)*; IEEE: New York, NY, USA, 2022; pp. 186–190.
- Choustoulakis, E.; Pastelakos, E. AI-driven analysis of game tactics and player performance. In *Proceedings of the 17th Annual International Conference of Education, Research and Innovation, Seville, Spain, 11–13 November 2024*; pp. 3350–3359.
- George, A.S.; George, A.H. The AI job revolution-how emerging roles are reshaping the future of work and creating new career pathways. *Partn. Univers. Innov. Res. Publ.* **2025**, *3*, 58–70.

10. Bezzina, S.; Dingli, A. My teammate is an AI: Evaluating generative AI in game asset creation through a post-gamejam study. In *Conference Proceedings of DiGRA 2025: Games at the Crossroads*; DiGRA: Tampere, Finland, 2025.
11. Thomas, B. Autonomous quality assurance: Leveraging generative AI agents for functional testing of cloud-native applications. *J. Comput. Sci. Technol. Stud.* **2025**, *7*, 747–754.
12. Doyle, S. Generative AI and illustration: Questions from the field. *J. Illus.* **2024**, *11*, 165–189.
13. Panchanadikar, R.; Freeman, G. I’m a solo developer but AI is my new ill-informed co-worker: Envisioning and designing generative AI to support indie game development. *Proc. ACM Hum.-Comput. Interact.* **2024**, *8*, 1–26.
14. Kumari, N.V.; Ghantasala, G.P.; Ananthanagu, U.; Vidyullatha, P.; Khan, M. The impact of generative AI in gaming: Exploring immersive experiences. In *Generative AI: Disruptive Technologies for Innovative Applications*; John Wiley & Sons: Hoboken, NJ, USA, 2025; pp. 107–130.
15. Coe, N.M.; Yang, C. Mobile gaming production networks, platform business groups, and the market power of china’s tencent. *Ann. Am. Assoc. Geogr.* **2022**, *112*, 307–330.
16. Partners, N. *China Games Market Report 2025*; Niko Partners: Campbell, CA, USA, 2025.
17. Lu, X. The legal boundaries of creativity: Exploring how China’s copyright law regulates AI-generated content in video game development. *Int. J. Cult. Policy* **2026**, 1–19.
18. Amankwah-Amoah, J.; Appiah, G. Unmasking the silent threat: AI-induced human capital obsolescence and business failure. *J. Manag. Psychol.* **2025**, *40*, 586–603.
19. Stige, Å.; Zamani, E.D.; Mikalef, P.; Zhu, Y. Artificial intelligence (AI) for user experience (UX) design: A systematic literature review and future research agenda. *Inf. Technol. People* **2024**, *37*, 2324–2352.
20. Lao, Q. A systematic review of AI-driven game design and user experience research. *Humanit. Soc. Sci. Res.* **2025**, *8*, 229–229.
21. Aliyu, M.B. Efficiency of boolean search strings for information retrieval. *Am. J. Eng. Res.* **2017**, *6*, 216–222.
22. Gusenbauer, M.; Haddaway, N.R. Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of google scholar, pubmed, and 26 other resources. *Res. Synth. Methods* **2020**, *11*, 181–217.
23. Acemoglu, D.; Restrepo, P. Automation and new tasks: How technology displaces and reinstates labor. *J. Econ. Perspect.* **2019**, *33*, 3–30.
24. Autor, D.H.; Levy, F.; Murnane, R.J. The skill content of recent technological change: An empirical exploration. *Q. J. Econ.* **2003**, *118*, 1279–1333.
25. Frey, C.B.; Osborne, M.A. The future of employment: How susceptible are jobs to computerisation? *Technol. Forecast. Soc. Change* **2017**, *114*, 254–280.
26. Engel, C.; Ebel, P.; Leimeister, J.M. Cognitive automation. *Electron. Mark.* **2022**, *32*, 339–350.
27. Ramachandran, K.; Mary, A.A.S.; Hawladar, S.; Asokk, D.; Bhaskar, B.; Pitroda, J. Machine learning and role of artificial intelligence in optimizing work performance and employee behavior. *Mater. Today Proc.* **2022**, *51*, 2327–2331.
28. Bakhshi, H.; Frey, C.B.; Osbourne, M. *Creativity vs. Robots: The Creative Economy and the Future of Employment*; Technical Report; Nesta: London, UK, 2015.
29. Jones, C.; Lorenzen, M.; Sapsed, J. Creative industries. In *The Oxford Handbook of Creative Industries*; Academic Press: Cambridge, MA, USA, 2015; pp. 3–32. <https://doi.org/10.4135/9781473911826.n6>.
30. Acemoglu, D.; Restrepo, P. Unpacking skill bias: Automation and new tasks. *AEA Pap. Proc.* **2020**, *110*, 356–361. <https://doi.org/10.1257/pandp.20201063>.
31. Autor, D.H. The “task approach” to labor markets: An overview. *J. Labour Mark. Res.* **2013**, *46*, 185–199.
32. George, A.S. Artificial intelligence and the future of work: Job shifting not job loss. *Partn. Univers. Innov. Res. Publ.* **2024**, *2*, 17–37.
33. Fügner, A.; Walzner, D.D.; Gupta, A. Roles of artificial intelligence in collaboration with humans: Automation, augmentation, and the future of work. *Manag. Sci.* **2026**, *72*, 538–557.
34. Bessen, J. Automation and jobs: When technology boosts employment. *Econ. Policy* **2019**, *34*, 589–626.
35. Aldasoro, I.; Gambacorta, L.; Pal, R.; Revoltella, D.; Weiss, C.; Wolski, M. *AI Adoption, Productivity and Employment: Evidence from European Firms*; EIB Working Papers No. 2026-02; European Investment Bank (EIB): Luxembourg, 2026.
36. Yotzov, I.; Barrero, J.M.; Bloom, N.; Bunn, P.; Davis, S.J.; Foster, K.M.; Jalca, A.; Meyer, B.H.; Mizen, P.; Navarrete, M.A.; et al. *Firm Data on AI*; Working Paper 34836; National Bureau of Economic Research: Cambridge, MA, USA, 2026.
37. Hemraj, S. Maximizing efficiency in game development through art styles, AI integration, and creative expression. *Loading* **2025**, *17*, 56–78.
38. Autor, D.; Salomons, A. *Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share*; Technical Report; National Bureau of Economic Research: Cambridge, MA, USA, 2018.
39. Fernández-Villaverde, J.; Mandelman, F.; Yu, Y.; Zanetti, F. The “matthew effect” and market concentration: Search complementarities and monopsony power. *J. Monet. Econ.* **2021**, *121*, 62–90.

40. Wang, W.-F.; Lee, T.-Y.; Lu, C.-T.; Hsu, C.-W.; i Campanyà, N.P.; Chen, Y.; Chen, M.Y.; Chen, B.-Y. Gentune: Toward traceable prompts to improve controllability of image refinement in environment design. In *Proceedings of the 38th Annual ACM Symposium on User Interface Software and Technology*; ACM: New York, NY, USA, 2025; pp. 1–21.
41. Liang, Y.; Luo, K.; Chen, X.; Chen, R.; Yan, H.; Li, W.; Liu, J.; Tian, F.P.; Tan, P. Unitex: Universal high fidelity generative texturing for 3D shapes. *arXiv* **2025**, arXiv:2505.23253.
42. Chen, Y.; Pan, Y.; Yang, H.; Yao, T.; Mei, T. Vp3d: Unleashing 2D visual prompt for text-to-3D generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Seattle, WA, USA, 17–21 June 2024; pp. 4896–4905.
43. Yıldırım, E.; Küçük, F.S. Comparative analysis of text-To-3D AI tools in urban furniture design: Evaluating Luma Genie, Meshy, Tripo, and DeepAI. *Megaron* **2026**, *21*, 90–100. <https://doi.org/10.14744/megaron.2026.47886>.
44. Boonchoo, S. The comparative study of artificial intelligence techniques: Deepmotion vs. autodesk maya in enhancing 3D animation creation and learning experiences. In *Proceedings of the 2025 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON)*, Nan, Thailand, 29 January–1 February 2025; pp. 489–492.
45. Khalloufi, H.; Zaifri, M.; Benlahbib, A.; Kaghat, F.Z.; Azough, A. Evaluating the accuracy of cloud-based 3d human pose estimation tools: A case study of motio by radical. *Int. J. Adv. Comput. Sci. Appl.* **2024**, *15*, 43–54.
46. AlSagri, H.S.; Farhat, F.; Sohail, S.S.; Saudagar, A.K.J. ChatGPT or Gemini: Who makes the better scientific writing assistant? HS AlSagri et al. *J. Acad. Ethics* **2025**, *23*, 1121–1135.
47. Serra, C.B.; Serra, G.M.B.; de Classe, T.M. Digital game development using large language models (LLMs): An exploratory study. In *Anais do Simpósio Brasileiro de Jogos e Entretenimento Digital (SBGames)*; Sociedade Brasileira de Computação: Porto Alegre, Brazil, 2025; pp. 538–549. <https://doi.org/10.5753/sbgames.2025.9992>.
48. Almalki, S.S. AI-driven decision support systems in agile software project management: Enhancing risk mitigation and resource allocation. *Systems* **2025**, *13*, 208.
49. Chaudhry, F.A. AI-powered decision-making: Balancing automation and human oversight in corporate governance. *Int. J. Bus. Comput. Sci.* **2024**, *1*, 7–10.
50. Anysphere, Inc. *Cursor: The AI Coding Platform*; Anysphere, Inc.: San Francisco, CA, USA, 2026.
51. Anthropic, P.B.C. *Claude by Anthropic*; Anthropic, P.B.C.: San Francisco, CA, USA, 2026.
52. Kotsiantis, S.; Verykios, V.; Tzagarakis, M. AI-assisted programming tasks using code embeddings and transformers. *Electronics* **2024**, *13*, 767.
53. Ali, K.Y.; Akter, S.; Islam, S.; Mridha, M.E. Advancing computational intelligence: AI-based algorithm design and optimization in programming. *J. Comput. Sci. Technol. Stud.* **2025**, *7*, 122–138.
54. Pai, K.; Devanbu, P.; Ahmed, T. Codocbench: A dataset for code-documentation alignment in software maintenance. In *Proceedings of the 2025 IEEE/ACM 22nd International Conference on Mining Software Repositories (MSR)*, Ottawa, ON, Canada, 28–29 April 2025; pp. 451–455.
55. Theunissen, T.; Hoppenbrouwers, S.; Overbeek, S. Approaches for documentation in continuous software development. *Complex Syst. Inform. Model. Q.* **2022**, *32*, 1–27.
56. Akbar, M.R. The accuracy of AI-generated code towards productivity. In *2025 International Conference on Converging Technology in Electrical and Information Engineering (ICCTEIE)*; IEEE: New York, NY, USA, 2025; pp. 106–111.
57. Hibi, W. How AI tools influence the skills of young developers. *Int. J. Multicult. Educ.* **2025**, *27*, 33–52.
58. Martínez García, G. *AI-Powered Project Management: Unleashing the Potential of Intelligent Systems for Efficient Group Coordination and Project Execution*; Technical Report; Universitat Politècnica de Catalunya: Barcelona, Spain, 2024.
59. Farhan, K.A.; Asadullah, A.; Kommineni, H.P.; Gade, P.K.; Venkata, S. Machine learning-driven gamification: Boosting user engagement in business. *Glob. Discl. Econ. Bus.* **2023**, *12*, 41–52.
60. Mandliya, R.; Goel, L. AI techniques for personalized content delivery and user retention. *Int. J. Multidiscip. Innov. Res. Methodol.* **2024**, *3*, 218–244.
61. Zhao, J. A multi-level intelligent control and deep learning-based personalized game content recommendation: Signal processing and sensor data fusion in distributed intelligent systems framework. In *2025 5th Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS)*; IEEE: New York, NY, USA, 2025; pp. 1108–1112.
62. Hossan, M.M.; Fouda, M.M.; Eishita, F.Z. Adaptive game design using machine learning techniques: A survey. In *2024 IEEE International Conference on Internet of Things and Intelligence Systems (IoTIS)*; IEEE: New York, NY, USA, 2024; pp. 144–150.
63. Lee, J.; Yoon, S.; Shim, H.; Yoo, Y. Development of an llm-based chatbot to support learnability in stardew valley: A diary study approach. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*; ACM: New York, NY, USA, 2025; pp. 1–19.
64. Diaz-Garcia, J.A.; Carvalho, J.P. A literature review of textual cyber abuse detection using cutting-edge natural language processing techniques: Language models and large language models. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2025**, *15*, e70029. <https://doi.org/10.1002/widm.70029>.

65. Stouffer, D. *Broken Ladder:: The Collapse of Entry-Level Jobs in a World Transformed by Autonomous AI Agents*; Balboa Press: Bloomington, IN, USA, 2025.
66. Alharthi, S.A. Generative AI in game design: Enhancing creativity or constraining innovation? *J. Intell.* **2025**, *13*, 60.
67. Pandhare, H.V. From test case design to test data generation: How AI is redefining qa processes. *Int. J. Eng. Comput. Sci.* **2024**, *13*, 26737–26757.
68. Zeytin, E.; Köseenciğ, K.Ö.; Öner, D. The role of AI design assistance on the architectural design process: An empirical research with novice designers. *J. Comput. Des.* **2024**, *5*, 1–30.
69. Willard, J.; Jia, X.; Xu, S.; Steinbach, M.; Kumar, V. Integrating scientific knowledge with machine learning for engineering and environmental systems. *ACM Comput. Surv.* **2022**, *55*, 1–37.
70. Fierro, L.E.; Caiani, A.; Russo, A. Automation, job polarisation, and structural change. *J. Econ. Behav. Organ.* **2022**, *200*, 499–535.
71. Erickson, K. AI and work in the creative industries: Digital continuity or discontinuity? *Creat. Ind. J.* **2024**, 1–21.
72. Taeihagh, A. Governance of generative AI. *Policy Soc.* **2025**, *44*, 1–22.
73. Xie, Y.; Xie, Y. When artificial intelligence makes everything similar: The risks of content homogenization. *Chin. J. Sociol.* **2026**, *12*, 157–172.
74. Anderson, B.R.; Shah, J.H.; Kreminski, M. Homogenization effects of large language models on human creative ideation. In *Proceedings of the 16th Conference on Creativity & Cognition*; ACM: New York, NY, USA, 2024; pp. 413–425.
75. Esiri, S. A digital innovation model for enhancing competitive gaming engagement and user experience. *Int. J. Multidiscip. Res. Growth Eval.* **2022**, *3*, 752–760.
76. Hutson, J. From displacement to design: Reframing work, skills, and education for the AI-transformed economy a review. *ISRG J. Econ. Financ.* **2025**, *2*, 760.
77. Ghosh, A.; Nair, A.A.; Sri, A.L.J.; Vijay, M.; Kajavinthan, K. The paradox of AI and creativity: Enhancing or hindering innovation? In *Data-Driven AI: A Multidisciplinary Approach*; CRC Press: Boca Raton, FL, USA, 2026; pp. 99–113.
78. Sivarethinamohan, R.; Aranganathan, P.; Sujatha, S.; Chithra, M.; Sheela, S.C. The power of AI-driven technological development on the working environment and decision-making process in the digital landscape. In *International Conference on Extended Reality*; Springer: Berlin/Heidelberg, Germany, 2025; pp. 40–57.
79. Abbasi, B.N.; Wu, Y.; Luo, Z. Exploring the impact of artificial intelligence on curriculum development in global higher education institutions. *Educ. Inf. Technol.* **2025**, *30*, 547–581.
80. Arora, A.K.; Kumar, A.; Tyagi, R.; Sharma, S.; Kumar, A.; Kumar, S. Future of education with AI-assisted technologies. In *Artificial Intelligence in Peace, Justice, and Strong Institutions*; IGI Global Scientific Publishing: Hershey, PA, USA, 2025; pp. 169–190.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.