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The mediating role of artificial intelligence in the relationship between production team productivity, quality management, and digital content production efficiency

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ABSTRACT

This study investigates the role of Artificial Intelligence (AI) in improving team productivity, quality management, and production efficiency in 3D game animation. The study aims to examine how AI influences workflows, team skill levels, and overall production outcomes in the animation industry. A quantitative survey was conducted among professionals working in medium- and large-sized animation companies, and the collected data were analyzed using Structural Equation Modeling (SEM). The results indicate that AI significantly improves quality management by automating quality control processes and providing real-time insights, which enhance production standards. However, AI shows a limited direct effect on production efficiency, suggesting that its full potential has not yet been fully realized in current workflows. The findings also highlight the importance of team skill levels, as highly skilled teams are better able to integrate AI tools into their workflows and gain greater benefits from AI adoption. The study is limited to medium- and large-sized animation companies, and therefore the findings may not fully represent smaller firms. In addition, the cross-sectional research design limits the ability to establish causal relationships. Future research could apply longitudinal designs and include objective performance data to provide more comprehensive insights. The results suggest that animation companies should prioritize training and professional development to effectively utilize AI technologies, while ensuring that human expertise remains central to the creative process. The integration of AI in animation production may lead to more efficient workflows, reduced operational costs, and improved product quality, which can support innovation, improve the working environment, and contribute to the creation of high-quality digital content for global audiences.

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1. Introduction

AI in 3D game animation represents a breakthrough approach to enhancing team efficiency and quality. Traditional animation methods are labor-intensive and resource-consuming, making it challenging to balance time and quality. Recent discoveries suggest that artificial intelligence may automate complex tasks, such as motion capture, to enhance these procedures. It would boost production efficiency and save operational costs. As teams become more comfortable with this technology, their skill levels improve, which in turn enhances animation quality and fosters an environment of ongoing education. Artificial intelligence mediates manufacturing efficiency, affecting productivity and quality management. For example, AI-driven mechanisms may review workflows and provide data-driven insights, helping teams enhance their processes and artistic output (Javaid et al., 2022). Synergy provides animators with greater freedom and aligns with creative industry trends that value adaptation and originality. Thus, it is crucial to study the integration of artificial intelligence and its effects on 3D character animation productivity, quality, and skill development.

AI-powered technologies are changing 3D game animation development. AI is becoming increasingly important for improving efficiency and quality in creative industries like gaming. It automates tedious tasks, such as character modeling and animation

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rigging, streamlining workflows and allowing animators to focus on creativity. Artificial intelligence can optimize production time and resources to enhance worker productivity, according to studies. This is especially true for AI-powered commercial solutions. AI's capacity to analyze large datasets helps develop a deeper understanding of client preferences, enabling the creation of more personalized content. Advanced artificial intelligence frameworks that aid creative decision-making demonstrate this value. These frameworks effectively connect art and technology. The gaming industry is growing more competitive. Thus, teams that wish to maximize their animation production efforts must understand how artificial intelligence affects efficiency and quality control.

The contradiction of increased quality standards and short development cycles makes 3D game animation production efficiency optimization exceedingly more complex. These two reasons exacerbate this difficulty. Inefficiencies from obsolete procedures generate delays and higher production expenses for many animation teams (Schwarzer et al., 2023). Even though technology has advanced. Although artificial intelligence (AI) offers potential solutions, the lack of empirical research on its moderating effects on productivity and quality management is a significant concern. A gap in our understanding of how artificial intelligence might raise production and animation quality by improving team expertise and experience. The proper integration of AI technologies into existing processes may result in pushback from team members accustomed to traditional methods, which can lower productivity and engagement. According to Han et al. (2019), the most significant question is how to combine artificial intelligence with human creativity and technical skill to create an effective production environment. The gaming industry must focus on how artificial intelligence affects team efficiency and quality management in the creation of 3D game animations to remain competitive. The gaming business must overcome these interrelated issues to grow.

Despite the growing body of research on artificial intelligence and 3D game animation, there is still a lack of understanding about human-AI collaboration in creative teams. Artificial intelligence has shown promise in improving productivity and quality management, but its adoption may affect team relationships and performance. The effectiveness of feedback mechanisms in virtual teams utilizing artificial intelligence is unknown. AI subjective input can positively or negatively impact team morale and output. Current research emphasizes the need for customized training methodologies to instruct teams on how to work with AI systems effectively. These frameworks are restricted, highlighting the need for empirical research on collaborative training approaches. Few studies have examined the temporal and environmental factors that affect team decision-making with artificial intelligence (Yan and Gurkan, 2023). Artificial intelligence capabilities are also disputed. Elshan et al. (2022) warned that overreliance on intelligent systems might reduce team members' initiative and accountability. We must understand these complex linkages to integrate artificial intelligence effectively into creative processes. Understanding is essential for improving teamwork and preserving the intrinsic inventiveness of 3D animation.

This study examines how AI affects the efficiency of 3D game animation production in two ways. This will be achieved by examining how AI impacts team productivity, quality management, and skill levels. This research examines the impact of AI on the relationship between these distinct characteristics and production efficiency, with a focus on optimizing the utilization of AI in creative processes.

This study can help us comprehend how AI can transform 3D game animation by enhancing team efficiency and quality management. Since the gaming industry expects high-quality items in shorter timeframes, effective systems that can integrate artificial intelligence into current processes are needed. By providing empirical evidence on how artificial intelligence affects creative processes and the quality of output, this research aims to fill gaps in the academic literature and practical applications (Peters et al., 2020). The research also aims to gain a deeper understanding of creative industry collaboration, which has been largely overlooked in the literature (Perera et al., 2022). This will be done via studying AI and team dynamics. The study of these traits fosters creativity and efficiency in animation studios, providing frameworks for utilizing technology while preserving artistic integrity. Finally, parties seeking process optimization will benefit from this research. It will also contribute to the theoretical discourse on how artificial intelligence is transforming creative domains, allowing it to meet essential needs for sustainable and prosperous game production practices (Ochsner, 2024).

2. Literature review

The relationship between AI, production team productivity, quality management, team skill levels, and production efficiency is complex, especially in the context of 3D game animation. In this review, synthesize existing literature to explore the roles of AI in enhancing these key areas, focusing on where studies agree, where they conflict, and how this informs the hypotheses and conceptual model of the present study.

2.1. Production team productivity

The productivity of the production team should be studied extensively, especially in agile development frameworks, where quick responsiveness to changing needs is essential. Well-structured agile teams can boost productivity by enhancing cooperation and communication. Mashmool et al. (2021) developed a statistical model that suggests inter-team connections, team vision, and leadership significantly impact the productivity of agile software teams. These findings suggest that team members should be included in workflow changes to create a high-performance environment (Hysong et al., 2019). Teamwork is a key factor in organizational efficiency, according to Adhikari (2020), who emphasized the importance of common behaviors in achieving goals. Several studies have examined productivity factors, and all of them show a strong correlation with individual and collective engagement, suggesting that improving team relations is crucial (Verbruggen et al., 2019). Agile methodologies are growing more popular, but there are few ideas on how to adapt them to different teams. This suggests a need for a unified model that considers several productivity factors (Tavakoli and Gandomani, 2018). The research emphasizes the need for continued investigation into factors that enhance productivity in agile teams with varying setups (Uribe et al., 2022).

2.2. Quality management

Quality management is crucial to production efficiency in many industries. It includes methods to meet consumer expectations while enhancing product quality and company efficiency. Azouza and Masaud (2023) found that comprehensive quality management can significantly enhance quality control systems within organizations. This ensures that product standards align with client needs. Ametova et al. (2023) stated that integrated management systems indicate a shift toward industry-specific quality management frameworks that improve operational efficiency. Total Quality Management (TQM) emphasizes product quality and corporate culture (Osazevbaru and Oyibo, 2023). It boosts staff engagement and consumer satisfaction. Effective quality management systems are crucial for maintaining competitiveness, meeting increasing demands, and enhancing performance across all industries (Czerwińska and Pacana, 2022).

2.3. Team skill level and expertise

When evaluating collaborative projects, the skills and expertise of team members are crucial. This is especially true in complex fields such as healthcare and technology. New research has highlighted expertise asymmetry, which indicates that a team's dynamics and performance are significantly influenced by both individual team members' competence and their variations in expertise (Burtscher et al., 2020). It emphasizes the importance of team communication and cooperation in maximizing individual skill sets. Leadership methods that encourage group learning and information sharing have also been shown to improve group performance and confidence (El Achi, 2024). Integrating team members' abilities increases improvisation and adaptability, which are crucial in unpredictable circumstances. Teams require both technical and non-technical skills, such as interpersonal and communication skills, to work effectively together (Schmutz et al., 2019). Teams need technical and non-technical skills. According to Ballangrud et al. (2020), collaboration-focused training programs enhance team performance, underscoring the importance of ongoing team development. An environment that emphasizes skill development and individual cooperation is crucial for maximizing team productivity and achieving high-quality results in various organizational settings.

2.4. Artificial intelligence

AI has transformed team relationships and collaboration processes across various sectors. The increasing use of artificial intelligence in teams highlights the need to investigate how human-AI interaction impacts work efficiency and effectiveness. Flathmann et al. (2024) found that teams adapting to artificial intelligence technologies require specific training in collaboration and coordination. Explainable AI may enhance perceived trustworthiness, thereby promoting human-AI collaboration (Georganta and Ulfert, 2024). AI may also boost team sizes in high-tech and customer relationship management contexts. AI improves operational performance and consumer experiences (Chen, 2024). However, developing AI roles in teams requires rigorous examination of AI's unique capabilities, such as task execution and decision-making (Siemon, 2022). It requires teams to have the tools to maximize their skills. Thus, understanding the multifaceted impact of artificial intelligence on team performance illuminates its pros and cons. Utilizing AI's potential requires a deeper understanding of effective management and team structures (Darban, 2024). In many organizational settings, collaborative frameworks will boost productivity and team performance (Piorkowski et al., 2021).

2.5. Production efficiency

Production efficiency is crucial to an organization's effectiveness in many domains, including supply chain management and manufacturing. Colicchia et al. (2019) found that manufacturing efficiency increases competitiveness and can significantly reduce operating costs. Sharing supply chain data boosts operational efficiency (Chen et al., 2019). This knowledge has been proven to be highly relevant in the fashion industry. The use of cutting-edge technologies, such as the Internet of Things (IoT) and blockchain, in agro-food supply chains has enhanced information exchange and traceability, thereby improving production processes. Analysis of production efficiency using the Malmquist Index can reveal variations in productivity over time, revealing key areas for improvement (Li and Wang, 2022). Because companies that actively integrate quality controls throughout their supply chains achieve superior operational results, quality management systems enhance production efficiency (Yu and Huo, 2018). This is because these companies perform better. Agricultural efficiency is improved by optimizing human resources and enhancing supply chain communication. This illustrates how various factors can impact production. Focusing on information exchange, technical advancements, and quality control can boost production efficiency (Li et al., 2023).

2.6. Hypothesis development

As AI technologies become increasingly prevalent in workplaces, a theory on how AI affects productivity in production teams is crucial. AI enhances team productivity by enhancing job efficiency and facilitating seamless communication. Flathmann et al. (2024) found that automating repetitive tasks using AI can ease workflows. This enables team members to focus on more challenging and valuable tasks. However, an excessive dependence on artificial intelligence may reduce teamwork and motivation, resulting in poor performance if team members believe AI is taking over crucial tasks (Elshan et al., 2022). Thus, our premise is that AI enhances production team output by improving operational efficiency, but it must be balanced with human contributions to maintain collective engagement. To overcome the challenges of human-AI team dynamics, proper training and collaboration are essential (Yan and Gurkan, 2023). This dual strategy may yield improved production team outcomes by combining human intelligence with artificial intelligence.

Quality Management (QM) and AI are essential for understanding how AI can enhance quality control. Khinvasara et al. (2024) found that AI considerably improves QM by providing actionable insights and automating quality tests. It improves manufacturing efficiency and reduces errors. Rai et al. (2021) suggested that machine learning algorithms enable organizations to predict quality issues before they occur. This enables companies to use proactive management to maintain product quality.

Gonzalez-Garcia et al. (2024) suggested that integrating AI into quality management systems can improve stakeholder communication and streamline real-time data processing. This may foster a culture of continuous improvement and quality responsiveness across the organization. According to Naik et al. (2022), it is crucial to address biases and ethical challenges in artificial intelligence decision-making to achieve quality management goals without compromising integrity or transparency.

Moreover, Team Skill Level and Expertise highlight the need for human capability in AI technology use. This hypothesis posits that enhanced team competency leads to improved AI utilization, ultimately enhancing productivity and informed decision-making. Artificial intelligence technologies can automate routine activities and provide analytical support, but their efficacy depends on people's ability to analyze and act on the insights generated by AI (Davenport, 2018). Teams lacking technical skills may struggle to implement AI solutions, underscoring the need for ongoing training and development. As more companies adopt AI-driven approaches, they require a trained staff to manage their complexity (Fenwick et al., 2024). Our hypothesis suggests that teams with higher skill sets will have better results when using AI technologies in their operations. In dynamic contexts, such teams foster productivity and innovation.

To improve operational environments, ideas on the relationship between production team productivity and production efficiency must be developed within the context of AI integration. This hypothesis proposes that utilizing artificial intelligence to enhance production team productivity will improve production efficiency. AI helps teams automate tedious tasks and focus on critical production areas by optimizing operations (Rahman et al., 2025). As another point of interest, empirical studies have shown that adequate training and collaborative practices, which are impacted by artificial intelligence, improve team workflows and communication, thereby increasing productivity and decreasing cycle times (Olan et al., 2022). However, organizations must ensure that their personnel are skilled in artificial intelligence to reap these benefits, as implementing such technology without understanding may reduce productivity.

Quality management initiatives boost production efficiency. Effective quality management systems, such as Total Quality Management (TQM) and Lean Manufacturing, will streamline operations and reduce waste, thereby increasing productivity. Comprehensive quality management frameworks enable companies to identify inefficiencies and comply with quality requirements, thereby enhancing operational efficiency. AI-driven systems, like predictive maintenance and process optimization, have been shown to improve production efficiency by reducing downtime and resource wastage. Efficient quality management drives continuous improvement, which in turn reduces manufacturing errors and enhances market responsiveness (Geng et al., 2024). Thus, enterprises must emphasize quality management as a strategic focus to maintain competitive advantages in their industries and increase production efficiency. Seňová et al. (2021) emphasized the growing significance of quality in production processes, emphasizing the need to understand this dynamic for sustainability and operational excellence.

Team skill level, expertise, and production efficiency. Higher team expertise may boost production efficiency. This notion suggests that as team members enhance their skills and knowledge, they can better leverage resources and technology, thereby simplifying operations and reducing waste (Yoon and Zhu, 2022). The team's efficient use of its skills fosters cooperation, which is essential for identifying and addressing production process inefficiencies. Teams with strong transactive memory systems, in which members are familiar with each other's talents, can enhance operational performance by making decisions and solving problems more efficiently (Li et al., 2024). Because team members are familiar with each other's strengths, Caskurlu et al. (2024) suggested that concentrated skill development can enhance individual competencies and team relationships, thereby increasing production efficiency and organizational performance.

AI and Production Efficiency suggest that AI technology can enhance production processes across various sectors. AI can enhance resource allocation, streamline procedures, and reduce operating expenses, increasing manufacturing efficiency (Trakadas et al., 2020). Advanced analytics and machine learning methods allow AI systems to analyze enormous datasets. This helps them find inefficiencies and suggest adjustments, enabling proactive management and decision-making. Dmitrieva et al. (2024) suggested that artificial intelligence can enhance automation, thereby accelerating production, reducing waste and errors, and making production more environmentally friendly. Companies can better adapt to market requirements and maintain a competitive advantage when they utilize AI insights. This hypothesis suggests that businesses should invest in artificial intelligence strategies that support their production efficiency goals, while also considering the challenges of implementing these strategies (Ononokpono et al., 2023).

2.7. Theory

AI-based technologies boost industrial efficiency. Automating and streamlining tasks does this. This idea suggests that AI transforms industrial systems to improve workflows and resource allocation. Huang (2024) found that artificial intelligence boosts productivity by replacing labor and creating new job opportunities, but it has little long-term impact on labor employment. The dynamic nature of artificial intelligence enables real-time data analysis, predictive maintenance, and process optimization, thereby reducing downtime and increasing output. The framework also suggests that firms integrate AI technologies to achieve resilient performance and remain competitive in a changing market.

The Human-Centric Artificial Intelligence concept emphasizes how artificial intelligence technology and human labor boost worker productivity. Shchepkina et al. (2024) demonstrated that integrating AI technology into the workplace can enhance human abilities and promote innovation and responsiveness. Practical artificial intelligence automates mundane tasks, enabling workers to focus on higher-level responsibilities and thereby increasing job satisfaction and productivity. For a successful deployment, ethical considerations must be addressed, and AI must be tailored to the workforce's needs. The idea proposes a balanced approach to productivity, in which AI collaborates with humans while considering the socio-economic effects of automation on employment.

3. Methodology

3.1. Sampling and data collection

This quantitative, positivist study examines the impact of AI on team productivity and quality management in the 3D game animation industry. This project aims to understand how artificial intelligence technologies optimize production efficiency and improve animation team skills. AI-integrated animation studio expertise makes up the sample. This is because AI integration in this industry is still in its early stages. This research targets 3D game animators, production managers, and technical personnel. These individuals are directly impacted by AI technology and possess relevant knowledge in AI-enhanced processes. The sample comprises employees from large and medium-sized animation companies, ensuring a diverse range of AI experiences and their impact on production efficiency and quality management. Purposeful sampling ensures that the sample correctly represents the primary industrial stakeholders. This technique selects creative and technical 3D animation participants. Animators, riggers, character designers, and production supervisors are examples of these professionals. Participants must have one year of animation production AI experience. This ensures they experience both traditional and AI-enhanced workflows.

The data will be collected by sending an online survey to 3D animation specialists at various businesses. The survey will collect participants' experiences with AI and its effects on team productivity, quality management, and personal skill development. The poll will also collect personal information, including years of experience, team position, and involvement in AI-driven operations. The survey will include both closed-ended and open-ended questions to gain a comprehensive understanding of participants' experiences. Questions with closed-ended responses will assess how artificial intelligence affects productivity and quality.

In contrast, questions with open-ended responses will allow participants to share their own experiences and challenges with AI. Before being released to the public, a pilot test will be conducted with a small group of animation experts to ensure clarity and legitimacy. Using pilot test feedback will enhance the reliability and comprehensiveness of the survey instrument.

Power analysis using G*Power will determine the sample size for this study. With a significance level of 0.05 and a medium effect size of 0.15, the research aims for a sample size with 95% statistical power to yield the best findings (Fig. 1). To maximize response rates, the survey will be distributed via email. Data gathering will take place over two months, from March to April 2025. Final sample response rate will be at least 30%. The responses will be cleaned and assessed using SPSS and SmartPLS after data collection is complete. This investigation examines the impact of AI on team productivity, quality management, and skill development. Structural equation modeling (SEM) will be utilized in 3D game animation studios to investigate how AI impacts production efficiency and team dynamics.

Table 1 shows respondent demographics and displays information on gender, age, education level, experience, and employment type. Additionally, Table 1 includes descriptive statistics such as the mean, standard deviation, skewness, and kurtosis. It also shows frequencies and percentages. The sample consists of 53.3% males (130 people) and 46.7% females (114 people). The gender distribution mean is 1.47, and the standard deviation is 0.500. Despite a slight male bias, the positive skewness (0.132) and negative kurtosis (-1.999) indicate a balanced distribution. People of all ages responded. The largest group (29.9%) consists of individuals aged 35–44, comprising 73 people. With 68 people, 27.9% are between 25 and 34. Adults aged 18–24 (18.0%, 44), 45–54 (15.2%, 37), and 55+ (9.0%, 22) are smaller groupings. The mean age is 2.69 years, and the standard deviation is 1.193. The skewness of 0.291 indicates a slight rightward distribution, while the kurtosis of -0.729 suggests a flat age distribution. Master's degrees are the most common (47.1%, 115 people), followed by Bachelor's degrees (40.2%, 98 people). This shows that most participants are educated. Diplomas are held by 10.7% of people (26), while Doctorates are held by 2.0% of people (5).

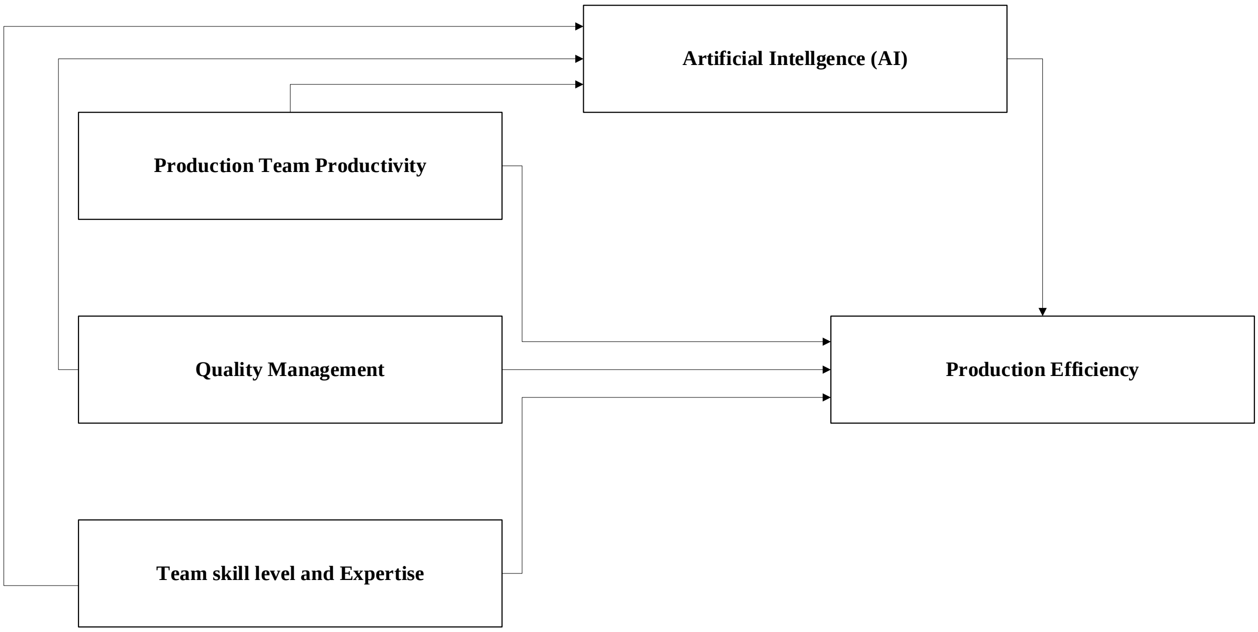

Fig. 1: Conceptual model

Table 1: Demographic profile of the respondents

Variable	Categories	Frequency	Percentage	Mean	Standard deviation (STDEV)
Gender	Male	130	53.3	1.47	0.500
	Female	114	46.7		
Age	18-24 years	44	18.0	2.69	1.193
	25-34 years	68	27.9		
	35-44 years	73	29.9		
	45-54 years	37	15.2		
	Above 55 years	22	9.0		
Level of education	Diploma	26	10.7	2.41	0.705
	Bachelor's degree	98	40.2		
	Master's degree	115	47.1		
	PhD	5	2.0		
	Others				
How many years working in current job	Less than 1 year	54	22.1	2.23	0.829
	1-3 years	88	36.1		
	3-5 years	94	38.5		
	6-7 years	8	3.3		
Employment type	Full-time	203	83.2	1.17	0.375
	Part-time	41	16.8		

The mean educational level is 2.41, and the standard deviation is 0.705. The skewness of -0.407 shows a leftward tilt, while the kurtosis of -0.464 implies an equally spread educational background. Several employees have worked there for three to five years (38.5%, 94 people), followed by those who have worked there for one to three years (36.1%, 88 people). Fewer people have worked for less than one year (22.1%, 54 people) than for six to seven years (3.3%, eight people). The mean standard deviation is

2.23. The skewness of -0.102 and kurtosis of -0.939 indicate a mostly normal distribution. Most responses are from full-time employees (83.2%, 203 people), and 16.8% are from part-time employees (41 people). Overall, respondents work full-time. The standard deviation is 0.375, and the average number of employees per position is 1.17. This category exhibits a peaked distribution with positive skewness (1.787) and kurtosis (1.202), which favors full-time workers. The sample has a well-rounded demographic distribution, with a majority of respondents aged 25–44, a full-time workforce, and higher education levels. The sample in this study is generalizable and diverse due to its balanced distribution of gender, age, education, and job experience.

Table 2 presents the descriptive statistics for the study's key variables. These factors include production team productivity, skill level and expertise, quality management, AI, and production efficiency. Table 2 displays the mean, standard deviation, skewness, and kurtosis for each variable, illustrating the response distribution. The production team's productivity in this variable has a mean score of 3.1811 and a standard deviation of 0.86703, indicating high response variability. The skewness of -0.239 suggests a modest leftward skew, indicating that most replies are on the higher end of the scale. Kurtosis of -0.277 indicates a flat distribution of answers, indicating no extreme values. Team expertise and skill: This variable indicates that respondents assess their team's competency as above average, with moderate variability, with a mean of 3.2557 and a standard deviation of 0.88304. This variable averages 3.2557. The skewness of -0.114 suggests a near-normal distribution with a slight trend toward lower values, while the kurtosis of -0.683 indicates a flatter distribution with no noticeable outliers. Both numerical values indicate dispersion. The management of quality respondent scores has an average of 3.1820, with a standard deviation of 0.91912. This suggests that most respondents think their teams use quality management practices. The skewness of -0.165 indicates an essentially symmetrical distribution, whereas the kurtosis of -0.786 indicates flatter replies without sharp peaks.

Table 2: Descriptive statistics

Variable	Mean	Standard deviation (STDEV)	Skewness	Kurtosis
Production team productivity	3.1811	0.86703	-0.239	-0.277
Team skill level and expert	3.2557	0.88304	-0.114	-0.683
Quality management	3.1820	0.91912	-0.165	-0.786
Artificial intelligence	3.2484	0.88543	-0.243	-0.480
Production efficiency	3.1566	0.98511	-0.082	-1.000

The average AI score is 3.2484, with a standard deviation of 0.88543. This suggests that AI boosts productivity, although perceptions vary widely. The distribution has a leftward skewness of -0.243, with answers clustering toward higher values. However, the kurtosis score of -0.480 shows fairly distributed replies with no outliers. Estimated production efficiency has a mean of 3.1566 and a standard deviation of 0.98511. The higher range in responses than other criteria suggests that respondents report limited manufacturing efficiency. The skewness score of -0.082 indicates that the distribution is almost symmetrical, indicating no outliers. However, the kurtosis of -1.000 indicates a flat distribution. The descriptive data indicate that respondents generally appreciated the productivity of the production team, talent level, quality management, artificial intelligence, and production efficiency. Most values for these variables are moderate to high. The distributions are mostly symmetric or slightly left-skewed, and there are no significant outliers, indicating that the variables distribute answers evenly.

3.2. Common method bias

To address potential standard method bias (CMB), this study implemented several strategies based on the recommendations of Podsakoff et al. (2012). Firstly, participants were assured that their responses would remain private and confidential and that the data would be used solely for research purposes. Secondly, the survey was designed in a way that the measurements were presented on separate pages, and explicit instructions were given for participants to read each statement carefully and respond honestly, emphasizing that the data would only be used for research purposes. Item ambiguity was minimized by defining unfamiliar terms and using specific questions (Tourangeau et al., 2000).

Additionally, to further assess the presence of CMB, Harman's single-factor test was conducted, involving a principal component factor analysis that included all primary constructs. This test was performed as a post-hoc analysis after data collection to examine whether a single factor accounted for most of the variance in the data. The results indicated that 38% of the data variance was explained by a single factor, which is less than the threshold of 50% (Fuller et al., 2016; Svensson et al., 2018). This suggests that standard method variance was not a significant concern in this study.

4. Data analysis and results

A preliminary analysis of the study data was conducted using SPSS version 24.0, which included examining missing values, outliers, means, medians, standard deviations, and normality assumptions. No missing values and outliers were found, while skewness values ranged from −2.214 to 0.289 and kurtosis values ranged from −1.284 to 7.433.

According to Kline (2011), the results indicated that non-normality did not severely affect parameter estimation and standard deviation of the model, as all absolute skew values were smaller than eight, and kurtosis was smaller than 10. As the data deviated from the assumption of multivariate normality, partial least squares structural equation modeling (PLS-SEM) was employed to test the hypotheses. Specifically, bootstrapping with 5000 resamples and a 95% bias-corrected confidence interval was employed to estimate the model (Byrne, 2016). The first stage of PLS-SEM involves assessing the measurement model to determine reliability and validity, while the second stage entails evaluating the structural model for hypothesis testing. Table 3 displays construct reliability and validity measurements for key study variables. AI, production efficiency (PE), production team productivity (PTP), QM, and team skill level (TS) are these variables. Table 3 displays Cronbach's alpha, composite reliability (rho_a and rho_c), and average variance extracted (AVE) for each construct, assessing the internal consistency and convergent validity of the measures. All constructs in the model were measured using multi-item scales. Items were adapted from established literature in the areas of team productivity, quality management, AI in organizations, and production/operational efficiency. They were refined to fit the specific context of 3D game animation and digital content production. Minor wording changes were made to ensure clarity and relevance for animation professionals. All constructs were measured using a five-point Likert scale, ranging from 1 (Strongly disagree) to 2 (Disagree), 3 (Neutral), 4 (Agree), to 5 (Strongly agree). The complete list of items is presented in Appendix A. The psychometric properties of these scales were evaluated using PLS-SEM. Cronbach's alpha, composite reliability (CR), and AVE values for all constructs met or exceeded commonly accepted thresholds ($\alpha \geq 0.70$, CR ≥ 0.70, AVE ≥ 0.50), indicating satisfactory reliability and convergent validity.

Table 3: Construct reliability and validity

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
AI	0.744	0.749	0.839	0.566
PE	0.751	0.755	0.843	0.575
PTP	0.732	0.733	0.848	0.651
QM	0.706	0.706	0.819	0.530
TS	0.753	0.755	0.835	0.504

AI's Cronbach's alpha is 0.744, indicating good internal consistency. The composite reliability values demonstrate the construct's reliability for rho_a (0.749) and rho_c (0.839), both of which exceed the internationally recognized threshold of 0.7. The AVE is 0.566, which is above the criterion of 0.5, indicating convergent validity. PE has a high Cronbach's alpha of 0.751, indicating internal consistency or dependability. Rho_a = 0.755 and rho_c = 0.843 indicate high composite dependability. This notion exhibits excellent convergent validity, as evidenced by PE's AVE of 0.575, which exceeds the threshold of 0.5. PTP is production team productivity. Cronbach's alpha for the PTP is 0.732, indicating reliability. Rho_a = 0.733 and rho_c = 0.848 support the construct's dependability. The AVE for PTP is 0.651, which is significantly above the requirement of 0.5, indicating remarkable convergent validity.

QM meets internal consistency standards, as indicated by a Cronbach's alpha of 0.706. However, the composite reliability scores (rho_a = 0.706, rho_c = 0.819) are below the desirable dependability threshold. QM exhibits appropriate convergent validity, as its AVE is 0.530, exceeding the threshold of 0.5. Cronbach's alpha for TS is 0.753, indicating strong internal consistency. Composite reliability ratings of 0.755 and 0.835 show build dependability. The minimal convergent validity requirements for TS are met by its AVE of 0.504. Cronbach's alpha and composite reliability are above the minimum permissible norms, indicating good internal consistency and convergent validity in the constructs. All constructs had AVE values of 0.5 or higher, proving the validity of this study's assessments. These findings suggest that the constructs used to evaluate AI, PE, PTP, QM, and TS are valid and trustworthy for this research.

Table 4 shows Fornell-Larcker discriminant validity results. This criterion assesses construct distinction. Off-diagonal numbers show construct correlations, whereas diagonal values show each construct's square root of AVE. Diagonals exhibit diagonal values. AI has a square root of the AVE of 0.752, indicating that it is distinct from other constructs. AI correlates with PE (r = 0.531), PTP (r = 0.364), QM (r = 0.708), and TS (r = 0.567). Artificial intelligence has adequate discriminant validity. This is because AI's association with each component is smaller than its square root AVE (0.752).

Table 4: Fornell-Larcker criterion

Constructs	AI	PE	PTP	QM	TS
AI	0.752				
PE	0.531	0.758			
PTP	0.364	0.485	0.807		
QM	0.708	0.608	0.418	0.728	
TS	0.567	0.697	0.456	0.674	0.710

The PE stands for production efficiency. PE's square root AVE is 0.758, confirming its independence. PE correlates with AI (r = 0.531), PTP (r = 0.485), QM (r = 0.608), and TS (r = 0.697). Since PE's correlation values are lower than its square root, it preserves its discriminant validity. PTP exhibits strong discriminant validity, as evidenced by its square root of the AVE of 0.807. Other factors associated with PTP include AI (0.364), PE (0.485), QM (0.418), and TS (0.456). Again, the correlation values are lower than the square root of the AVE, distinguishing the PTP from other factors. The square root of QM AVE is 0.728, indicating good discriminant validity. Compared to other variables, QM has significant associations with AI (r = 0.708), PE (r = 0.608), PTP (r = 0.418), and TS (r = 0.674). QM's uniqueness is supported by the fact that all correlation values are less than the square root of QM. The square root of the AVE for TS is 0.710, indicating good discriminant validity. TS correlates 0.567 with AI, 0.697 with PE, 0.456 with PTP, and 0.674 with QM. These are some correlated constructs. The concept's discriminant validity is assured by using the square root, much as correlation values are lower than TS's AVE. In general, the Fornell-Larcker criteria show that AI, PE, PTP, QM, and TS have strong discriminant validity. The fact that each group of constructs correlates smaller than the square root of their AVE values shows that they are distinct and do not overlap. This ensures that the measurement method used in this study is accurate and that the constructs are well-differentiated.

Table 5 shows saturated and estimated model fit statistics. These statistics can be used to assess the model's goodness of fit, ensuring that it accurately portrays the construct linkages. Both the saturated and estimated models have SRMR values of 0.077.

Table 5: Model fit

Constructs	Saturated model	Estimated model
SRMR	0.077	0.077
d_ULS	1.249	1.249
d_G	0.423	0.423
Chi-square	561.301	561.301
NFI	0.702	0.702

This result suggests a good match because it is below the 0.08 threshold. The SRMR statistic assesses the discrepancy between the observed and anticipated covariance matrices, with lower values indicating a more favorable model-data fit. Both the saturated and approximated models have d_ULS values of 1.249. This statistic measures the contrast between observed and predicted data. There is no set threshold for d_ULS, although lower values indicate a better fit, and in this case, the model fit is acceptable. Both the saturated and approximated models have d_G values of 0.423. Like d_ULS, d_G examines the difference between actual and expected data to measure model fit. When d_G is smaller, the model fits the data better and presents the data more accurately. Their Chi-square values are 561.301 for the saturated and estimated models. The Chi-square statistic evaluates model fit by comparing observed data to model predictions. The Chi-square test indicates that the model is accurate, with no significant differences between the observed and anticipated values. Even though the Chi-square test is sensitive to large sample sizes. The saturated and estimated models have the same NFI value of 0.702. NFI values of 0.90 or higher typically indicate a good model fit. With a score of 0.702, the model fit is decent but might be improved. High NFI values indicate a better model fit than a null model. The Normed Fit Index (NFI) for this model was calculated as 0.702. While this is above the threshold of 0.70, it is generally considered below the ideal cutoff value of 0.90, which would indicate a good fit. However, the NFI value suggests that the model may provide a better fit to the data. Despite this, the model is well-suited to reflect the study's structures and their interactions.

This study focused on AI and PE. The R^2 and modified R^2-Square values for these variables are presented in Table 6. These values indicate the proportion of each dependent variable's variance that can be attributed to the model's independent variables. Fig. 2 shows that the AI R-squared score is 0.518, indicating that the model's independent variables explain 51.8% of AI variance. The AI model has an adjusted R-squared value of 0.512. This parameter adjusts the R-squared for overfitting based on the model's predictor count. The revised R-squared value indicates that the model explains 51.2% of the variance in AI, which is significant and suggests that the model fits the data well. The R-squared value for PE is 0.550, indicating that the independent variables in the model explain 55% of the variance in PE. After accounting for the number of variables, the model explains 54.3% of the variance in PE with an adjusted R-squared of 0.543. This indicates that the model is a good fit, as the predictors account for a significant portion of the variation in PE. The R-squared and modified R-squared values for AI and PE indicate that the model can explain both variables. The independent variables account for roughly half of the variance in AI and PE, indicating that the model captures the most relevant factors affecting these constructs. These findings demonstrate that the model can explain correlations between variables.

Table 6: R-squared

Constructs	R-squared	R-squared adjusted
AI	0.518	0.512
PE	0.550	0.543

The overall impacts of the study constructs are presented in Table 7 and display the original sample values (O), sample mean (M), standard deviation (STDEV), T-statistics (|O/STDEV|), and P-values. These values help evaluate the relevance and strength of variable relationships. AI -> PE (Artificial Intelligence to Production Efficiency): The first sample result for AI's effect on PE is 0.096, with a mean of 0.097 and a standard deviation of 0.074.

Also, the sample mean is 0.097. However, the P-value is 0.195, and the T-statistic is 1.297. Since the P-value exceeds 0.05, this impact is not statistically significant. This indicates that AI has a limited impact on industrial efficiency. PTP -> AI (Production Team Productivity to Artificial Intelligence): The initial sample value for PTP's influence on AI is 0.051, with a sample mean of 0.052 and a standard deviation of 0.057. T is 0.907, while P is 0.365. The high P-value indicates that this correlation is not statistically significant, suggesting that Production Team Productivity does not significantly affect Artificial Intelligence in the research.

PTP -> PE (Production Team Productivity to Production Efficiency): With a sample mean of 0.182 and a standard deviation of 0.055, PTP's effect on PE starts around 0.180.

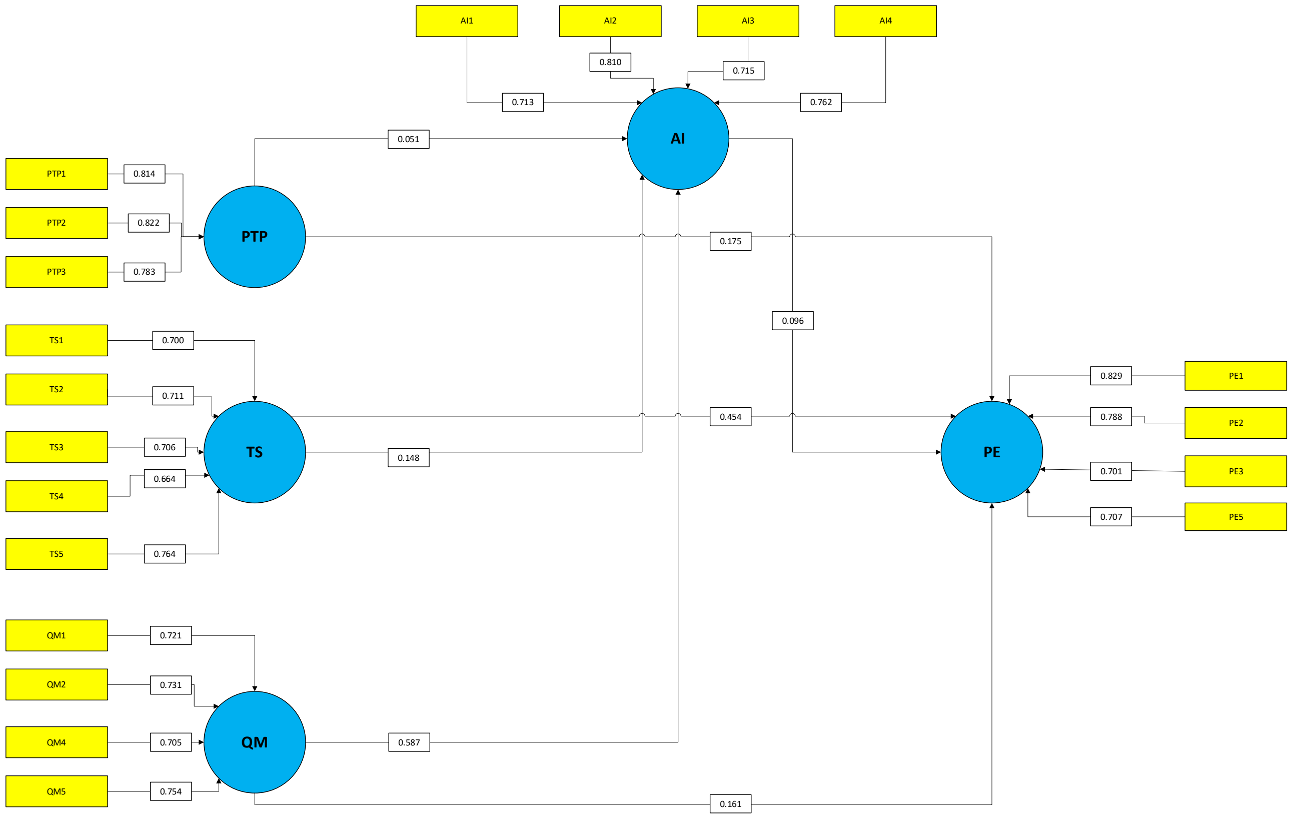

Fig. 2: Structural model

Table 7: Total effects

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
AI -> PE	0.096	0.097	0.074	1.297	0.195
PTP -> AI	0.051	0.052	0.057	0.907	0.365
PTP -> PE	0.180	0.182	0.055	3.288	0.001
QM -> AI	0.587	0.583	0.071	8.291	0.000
QM -> PE	0.217	0.218	0.072	3.013	0.003
TS -> AI	0.148	0.154	0.072	2.063	0.039
TS -> PE	0.468	0.470	0.070	6.701	0.000

Additionally, the sample mean is 0.182%. The P-value is 0.001, and the T-statistic is 3.288. This association is statistically significant because the P-value is less than 0.05. This shows that production team productivity strongly affects production efficiency. QM -> AI (Quality Management to Artificial Intelligence): The first sample value for QM's effect on AI is 0.587, with a mean of 0.583 and a standard deviation of 0.071. Additionally, the sample mean is 0.583. The P-statistic is 0.000, and the T-statistic is 8.291. Quality Management has a statistically significant effect on Artificial Intelligence, with a p-value of less than 0.05. QM -> PE (Quality Management to Production Efficiency): The first sample result for QM's effect on PE is 0.217, with a mean of 0.218 and a standard deviation of 0.072. Additionally, the sample mean is 0.218. The T-statistic is 3.013, and the p-value is 0.003. This effect is statistically correlated with production efficiency, suggesting that quality management improves production efficiency. TS -> AI (Team Skill Level to Artificial Intelligence): Initial sample value for TS's influence on AI is 0.148, with a sample mean of 0.154 and a standard deviation of 0.072.

Additionally, the sample mean is 0.154. However, the P-value is 0.039, and the T-statistic is 2.063. P-values below 0.05 imply a statistically significant association between Team Skill Level and AI. It is statistically significant. TS -> PE (Team Skill Level to Production Efficiency): With a sample mean of 0.470 and a standard deviation of 0.070, the first sample result for TS's effect on PE is 0.468. Also, the sample mean is 0.470. The P-value is 0.000, and the T-statistic is 6.701. This link is highly significant and has a low P-value, indicating that team competence has a strong effect on production efficiency.

Table 8 presents the indirect correlations between components, utilizing mediating variables from the research, and displays the original sample values (O), sample mean (M), standard deviation (STDEV), T-statistics (|O/STDEV|), and indirect impact P-values.

Table 8: Specific indirect effects

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
PTP -> AI -> PE	0.005	0.005	0.008	0.616	0.538
QM -> AI -> PE	0.056	0.056	0.043	1.300	0.194
TS -> AI -> PE	0.014	0.015	0.015	0.968	0.333

PTP -> AI -> PE (Production Team Productivity to Artificial Intelligence to Production Efficiency): The indirect impact sample mean is 0.005, and the standard deviation is 0.008. The starting sample value and sample mean for this effect are 0.005. The T-statistic is 0.616, and the P-value is 0.538. Because the P-value is greater than 0.05, this indirect influence is not statistically significant. This suggests that artificial intelligence does not directly affect production efficiency by impacting team productivity.

QM -> AI -> PE (Quality Management to Artificial Intelligence to Production Efficiency): This indirect impact sample mean was 0.056, and the standard deviation was 0.043. The original and mean sample values for this effect were 0.056. However, the P-value is 0.194, and the T-statistic is 1.300. The indirect effect of Quality Management on Production Efficiency using Artificial Intelligence is not statistically significant, as the P-value is greater than 0.05.

TS -> AI -> PE (Team Skill Level to Artificial Intelligence to Production Efficiency): Initial sample value for this indirect impact was 0.014 with a sample mean and standard deviation of 0.015. The sample mean included 0.015. T is 0.968, while P is 0.333. This indirect impact is also not statistically significant, indicating that Team Skill Level does not significantly affect Production Efficiency through the use of AI. Since the P-value exceeds 0.05, this is true.

5. Discussion

This study examined the role of AI in shaping team productivity, quality management, and production efficiency in the 3D game animation industry. The findings reveal several significant relationships, but they also show that AI did not significantly mediate the effects of team productivity, quality management, or team skill level on production efficiency. Understanding why these mediating effects are non-significant is crucial, especially given the growing assumption that AI directly accelerates production across industries. Animation production involves subjective judgement, artistic decision-making, and iterative refinement. Unlike manufacturing, where AI can automate structured tasks, creative work requires continuous interpretation and aesthetic evaluation. AI tools can support this process, but they cannot fully replace the creative discretion of animators or directors. Many AI-based tools for animation (e.g., AI-assisted rigging, motion prediction, and AI-driven cleanup) are not fully integrated across entire production pipelines. As a result, they provide localized support but do not yet influence overall production speed consistently enough to act as mediators. The strong relationship between AI and quality management suggests that AI contributes more to accuracy, standardization, and error reduction than to direct productivity gains. In animation, improving quality does not always result in shorter production times. In many cases, higher quality leads to additional refinement work, which may even slow down the process.

This study examines the impact of AI on team productivity, quality management, and production efficiency in the 3D game animation industry. The findings reveal both the indirect and mediating roles of AI in these processes, as well as the direct relationships between AI, team skill levels, and production efficiency. In this section, the most important findings are reviewed in relation to the current research, interpreted, and their implications for theory and practice are examined. This study found that AI had a limited direct effect on industrial efficiency, which was a significant finding. AI did not significantly increase PE (P = 0.195), suggesting that AI's inclusion in the animation production process does not directly enhance production efficiency. Research has shown that artificial intelligence may boost productivity by automating repetitive tasks, simplifying procedures, and cutting costs. AI tools can automate certain aspects of the production process, but animators and production teams may need time to adapt to the new technology before reaping the full benefits. Artificial intelligence may not be fully exploited or underused in the scenario studied, limiting its direct impact on industrial efficiency. However, the statistically significant relationship between AI and QM (P = 0.000) reveals that AI improves 3D animation quality management. Khinvasara et al. (2024) and Rai et al. (2021) found that artificial intelligence can foresee quality issues and automate quality checks, improving manufacturing standards. Since quality management improves both artificial intelligence and production efficiency, AI may contribute most to the production process by improving quality control mechanisms rather than operational efficiency.

TS improves artificial intelligence and manufacturing efficiency, another key breakthrough. TS significantly affected AI (P = 0.039) and manufacturing efficiency (P = 0.000). Talented teams are crucial to maximize AI's potential. Research has shown that expert human labor enhances the efficiency of AI applications. This study found that highly trained teams may be better equipped to integrate AI into their operations, thereby improving production quality and efficiency. Animation companies that wish to optimize AI use should prioritize personnel training and development. This will ensure their teams have the technical expertise to maximize AI's potential. PTP has a direct impact on PE (P = 0.001), indicating that higher team productivity leads to improved production efficiency.

Previous studies have demonstrated that effective communication, task delegation, and teamwork enhance productivity. Although PTP did not indirectly affect PE through AI, the direct result suggests that 3D game animation production efficiency may be improved through team cooperation and increased productivity. Despite significant direct effects, AI's indirect effects on production efficiency through PTP, QM, and TS were not statistically significant. PTP had no significant indirect influence on PE through AI (P = 0.538), whereas QM and TS had no significant mediation. Both findings match the prior studies. Despite its capacity to impact industrial efficiency, artificial intelligence may not be a major mediator in these pathways under the conditions analyzed. The intricacy of artificial intelligence's function in manufacturing may explain the lack of significant indirect impacts. AI may not mediate industrial efficiency as much as human inventiveness, decision-making, and adaptability.

This research sheds light on the intricate relationships between AI, team productivity, quality management, and production efficiency in 3D game animation. These data are compared to earlier studies, revealing several key insights. No direct influence of AI on PE was identified (P = 0.195). This contradicts prior studies that claimed AI might boost operational efficiency by automating activities and optimizing processes. The absence of a substantial link in this context may suggest that integrating artificial intelligence into production workflows requires time for adaptation and fine-tuning, and that its efficiency benefits may not be fully realized immediately.

QM significantly improves artificial intelligence (P = 0.000) and production efficiency (P = 0.003). This study suggests that artificial intelligence improves quality management systems by automating quality checks and providing real-time insights. The strong relationship between quality management and artificial intelligence suggests that AI's actual value in animation production may lie in improving quality control rather than operational efficiency. While integrating artificial intelligence, TS was found to affect AI significantly (P = 0.039) and production efficiency (P = 0.000). This analysis confirms prior results that competent human labor maximizes the use of artificial intelligence technology. Highly trained teams may better integrate artificial intelligence into their operations, improving manufacturing efficiency and quality.

PTP has a direct impact on production efficiency (P = 0.001). Teamwork, communication, and job delegation increase output, as shown by previous studies. The data indicate that team productivity is crucial to manufacturing efficiency, regardless of the use of AI. The study examined the indirect effects of artificial intelligence as a mediator between the constructs. They had no meaningful impact. P-values from 0.194 to 0.538 showed no significant indirect impacts between PTP, QM, TS, and AI-enabled production efficiency. Based on this, artificial intelligence, which improves industrial processes, may not be able to mediate these pathways in this study. This study contributes to the field of artificial intelligence research in the creative industries, with a focus on 3D animation. The direct impact of artificial intelligence on production efficiency may be limited in the medium term. However, its massive impact on quality management and its interaction with professional teams are crucial for animation companies looking to improve their production processes. Further research is needed to identify moderating factors that may enhance the efficiency of industrial AI. This study makes several important theoretical and practical contributions to the literature on AI in creative industries, particularly in the context of 3D game animation production.

Enhancing AI in Quality Management has been shown to boost production and efficiency across sectors. However, this study demonstrates how AI enhances the quality management of 3D game animation. This study found that AI greatly aids quality control. According to Khinvasara et al. (2024) and Rai et al. (2021), AI-driven automation increases quality assurance by predicting and eliminating manufacturing errors. This suggests that artificial intelligence may have a greater impact on industrial quality management than on operational efficiency. This study contributes to the growing body of literature on team skill levels and AI integration. The study supports the premise that artificial intelligence relies on human expertise to guide and enhance its use by demonstrating that teams with higher skill levels can better integrate AI into their operations. In studies on AI and productivity, the symbiotic relationship between human creativity and AI is becoming recognized. This emphasizes this relationship.

In highly creative fields, AI may be more valuable for enhancing quality than accelerating production. This contrasts with industrial automation theories. When tasks involve artistic judgment, AI cannot easily replace or significantly speed up human work. AI's effectiveness depends on how teams interpret, modify, and integrate its outputs. AI may first enhance quality management (as shown in this study), then gradually influence productivity as studios become more proficient with these tools.

The study challenges the idea that AI directly improves manufacturing efficiency. Artificial intelligence did not significantly mediate the relationship between production team productivity, quality management, and production efficiency. This study supports Handke et al. (2022), who found that the mediator role of artificial intelligence may vary depending on the context and application. This study shows that AI does not significantly mitigate these consequences in creative areas, adding complexity to our understanding of AI's role. This study also suggests studying the complex relationships between human skills and AI technologies. This work contributes to the underexplored subject of AI applications in creative domains, such as 3D game animation. The majority of artificial intelligence literature has focused on industrial or service industries (Tummala et al., 2025); however, this study contributes to the development of creative AI applications.

Animation companies seeking to enhance their production processes with AI should invest in AI technology and train their personnel to utilize it effectively. Training and skill development should be directed to ensure animators and production teams can fully benefit from artificial intelligence's ability to improve quality management and, to a lesser extent, production efficiency. Woodland et al. (2021) stated that this aligns with industry recommendations for continuous professional development in response to technological advancements. Increasing Production Efficiency through Teamwork: Since production team productivity significantly impacts production efficiency, studios should prioritize investing in team cooperation, effective communication, and efficient task management. AI can help, but it is also essential to recognize the value of traditional approaches, such as workflow optimization and leadership development, in enhancing team connections and efficiency. According to Mashmool et al. (2021) and Verbruggen et al. (2019), a well-rounded strategy that combines AI technology and improves team collaboration is needed. AI is most effective when applied to quality management rather than directly accelerating production. Investing in team skills is essential, as highly skilled teams extract more value from AI. Workflow optimization and teamwork remain irreplaceable drivers of efficiency. Studios should view AI as a long-term investment, expecting benefits to grow gradually rather than immediately.

The data suggest that AI can have a significant impact on improving output quality in quality management. Animation firms aiming to enhance production should focus on improving AI quality control systems. These include motion capture and animation error detection. Artificial intelligence can provide consistent, high-quality outputs, which is critical in the competitive gaming industry, where product quality is key. This study provides insights into how artificial intelligence technologies can be efficiently integrated into creative sectors, with implications for future technology integration in creative businesses. Artificial intelligence has the potential to stimulate creativity, but its impact on industrial efficiency may be delayed depending on how well teams adapt to new technologies. This conclusion is beneficial for firms considering artificial intelligence, as it emphasizes the necessity for sufficient training and adaptability to maximize its benefits. This work enhances our understanding of how artificial intelligence impacts quality management and team skill levels, and challenges the notion that AI enhances production efficiency. The research provides animation studios and other creative industries with practical advice on utilizing artificial intelligence, with a focus on talent development and team efficiency. This study advances the application of artificial intelligence in creative fields, laying the groundwork for future research and practice in this dynamic industry. Artificial intelligence continues to affect sectors.

This study sheds light on how AI affects 3D game animation, although it has certain drawbacks. Due to these constraints, future research may provide a deeper understanding of how artificial intelligence impacts team productivity, quality management, and production efficiency.

This study's sample size, which was limited to animation company professionals, was a significant limitation. The study scope is another restriction. Although the research encompasses a wide range of experiences, it may not accurately represent the sector. This is especially relevant given the proliferation of animation companies in various locations and their integration of AI. Smaller or less technologically advanced studios may have varied AI experiences, which may affect generalizability. Cross-sectional research was employed to collect data at a single point in time during the study. This hinders the ability to draw causal links between AI integration and manufacturing efficiency, quality management, or team productivity. Longitudinal research may reveal how AI integration evolves and how its effects change as teams become more proficient in AI. The study utilized self-reported data from industry professionals, which may have been biased by social desirability or recall bias. Professionals voluntarily provided data. Participants may have overestimated AI's efficacy or underestimated its challenges, resulting in a biased view of its impacts. Future studies may combine self-reports with objective performance data, such as production metrics and time tracking, to provide a more comprehensive and accurate evaluation.

To track the long-term effects of AI integration on production efficiency, team productivity, and quality management, longitudinal studies should be done. This would show how artificial intelligence affects teams over time and whether its benefits become clearer as they gain experience. Future research may encompass both large and small animation studios with varying levels of AI integration. This would improve the generalizability of findings. Future studio comparisons are possible. A comparison study may reveal how different studios utilize artificial intelligence, the challenges they encounter, and the distinct production and quality outcomes they achieve. This study focused on 3D game animation; however, the role of AI in cinema, VFX, and digital media remains understudied. Comparing these firms may help us understand how artificial intelligence affects creative processes and provide industry-wide insights on AI implementation. Future studies should investigate how business culture, leadership, and teamwork impact the effectiveness of AI integration. Practitioners seeking to enhance their AI workflows should understand how various studios incorporate AI, the challenges they encounter, and the strategies they employ to overcome them. Future research may enhance self-reported data with objective performance indicators. These include completion times, mistake rates, and quality assessments.

6. Conclusion

This study examined the impact of AI on team productivity, quality management, and production efficiency in the 3D game animation industry. This study sheds light on the direct and indirect effects of AI on animation production workflows. Empirical research provides these findings. The findings show that artificial intelligence enhances quality management by automating and standardizing industrial processes. However, its direct effect on production efficiency was limited, suggesting that artificial intelligence may not be sufficient alone to increase efficiency without complementary elements, such as competent teams and optimized processes. To effectively integrate and utilize AI technology, companies must invest in training and skill development. The fact that team skill levels were emphasized as a crucial factor in optimizing AI benefits shows the need for such expenditures. The research also revealed that the productivity of the production team significantly impacts production efficiency. Although artificial intelligence did not directly influence the interactions between other factors and production efficiency, team productivity and quality management showed clear benefits, underscoring the importance of human knowledge and cooperation in production. The research advances the theoretical understanding of artificial intelligence in creative sectors, particularly in 3D game animation. The report also advises animation companies on using AI to enhance quality management and productivity. Studios that prioritize technology and team growth may be better equipped to integrate artificial intelligence into their processes, creating a more efficient and high-quality production environment. However, further research is needed to determine the long-term effects of AI integration, its effects on creativity, and its potential applications in creative fields.

Appendix A. Survey instrument and measurement items

This appendix presents the full survey instrument used in the study, including all measurement items and scales for each construct. The questionnaire was structured into tables covering demographic information and key variables such as production team productivity, quality management, team skill level, artificial intelligence, and production efficiency, ensuring clarity and consistency in data collection.

Table A1: General information

No.	Questionnaire	Scale				
1	Gender		Male			Female
2	Age	18-24 years	25-34 years	35-44 years	44-54 years	55 years to Above
3	Level of education	Diploma	Bachelor's	Master's	Doctorate	Others
4	How many years working in current job	Less than 1 year	1-3 years	3-5 years	6-7 years	
5	Employment type	Full-time	Part-time			

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1	2	3	4	5

Table A2: Production team productivity (Kirkman and Rosen, 1999)

No.	Questionnaire	1	2	3	4	5
PTP1	To what extent do you believe that your team's communication facilitates productivity in your production processes?					
PTP2	How often does your team utilize collective problem-solving to enhance production outputs?					
PTP3	How effective are team meetings in addressing productivity challenges in production tasks?					
PTP4	Rate the flexibility of your production schedule in accommodating team suggestions for enhanced productivity.					
PTP5	How frequently does your team engage in training or skill development activities to enhance productivity?					
PTP6	In your opinion, how does your team's morale affect overall productivity levels in production?					

Table A3: Quality management (Robinson and Leonard, 2024)

No.	Questionnaire	1	2	3	4	5
QM1	How well do your organization's quality management practices align with production efficiency goals?					
QM2	To what extent does your organization use customer feedback to improve product quality?					
QM3	How frequently are quality assessments conducted in your production processes?					
QM4	Rate the effectiveness of cross-functional teams in maintaining quality standards across production stages.					
QM5	How often does your organization update its quality management practices based on market trends?					
QM6	How significant is the role of quality management training in enhancing production efficiency?					

Table A4: Team skill level and expertise (Peytcheva and Yan, 2025)

No.	Questionnaire	1	2	3	4	5
TS1	How confident are you in your team's ability to adapt to new technologies in production?					
TS2	To what extent does your team possess the skills necessary for effective collaboration?					
TS3	How often does your organization encourage knowledge sharing among team members?					
TS4	Rate your team's readiness to implement AI tools in enhancing production efficiency.					
TS5	How frequently do team members participate in professional development opportunities related to production skills?					
TS6	In your opinion, how does the diversity of skills within your team enhance overall performance?					

Table A5: AI (Hong et al., 2026)

No.	Questionnaire	1	2	3	4	5
AI1	How familiar are you with the AI technologies implemented in your production processes?					
AI2	To what extent do you believe AI has contributed to improving production efficiency in your organization?					
AI3	How often do you rely on AI-driven insights for decision-making in production tasks?					
AI4	Rate the effectiveness of AI systems in forecasting production needs and challenges.					
AI5	How significant do you think the challenges of AI integration are concerning production efficiency?					
AI6	In your opinion, what is the most significant benefit of AI adoption in your production processes?					

Table A6: Production efficiency (Fang et al., 2025)

No.	Questionnaire	1	2	3	4	5
PE1	To what extent do you believe that your organization's production processes utilize resources efficiently?					
PE2	How effectively does your organization allocate resources to minimize waste in production processes?					
PE3	How often are production goals met within the expected time frames in your organization?					
PE4	Rate the effectiveness of technology integration in enhancing your production efficiency.					
PE5	In your opinion, how significant has the role of employee training been in improving production efficiency?					
PE6	To what extent do you believe that quality management systems impact the efficiency of your production processes?					

List of abbreviations

AI	Artificial intelligence
AVE	Average variance extracted
CMB	Common method bias
CR	Composite reliability
d_G	Geodesic distance
d_ULS	Squared Euclidean distance
IoT	Internet of things
NFI	Normed fit index
PE	Production efficiency
PLS-SEM	Partial least squares structural equation modeling
PTP	Production team productivity
QM	Quality management
R^2	Coefficient of determination
SEM	Structural equation modeling
SPSS	Statistical package for the social sciences
SRMR	Standardized root mean square residual
TS	Team skill level
TQM	Total quality management

Compliance with ethical standards

Ethical considerations

Ethical approval for this study was obtained from the Research Ethics Committee of Lincoln University College. All participants were fully informed about the study's objectives, their right to confidentiality, and their ability to withdraw from the study at any time without consequence. Informed consent was secured from each participant prior to inclusion in the research. This study was conducted in accordance with the ethical guidelines outlined in the 1964 Declaration of Helsinki and its subsequent amendments.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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