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Article

The impact of AIGC on simulating realistic human movement for immersive learning in film and television education

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Abstract: This study investigates the impact of Artificial Intelligence Generated Content (AIGC) on teaching realistic human movement simulation in film and television education, with a focus on biomechanical principles. Through a 12-week randomized controlled study involving 46 students from three leading Chinese film academies, we examined the effectiveness of AIGC-based motion simulation systems compared to traditional teaching methods. Using a mixed-method approach, the study evaluated learning outcomes, technical accuracy, and user experience, emphasizing the biomechanical accuracy of simulated movements. Results demonstrated significantly higher performance in the AIGC group across multiple metrics, including motion accuracy (94.3% vs. 82.5%, $p < 0.001$), skill acquisition rates (improvement rate: 46.1% vs. 33.8%, $p < 0.001$), and knowledge retention (96.4% vs. 91.1%, $p < 0.001$). The AIGC system showed superior technical performance with 99.7% uptime and motion-to-photon latency below 20 ms, ensuring real-time responsiveness crucial for biomechanical training. Student engagement levels were notably higher in the AIGC group (92.4% vs. 78.6%, $p < 0.001$), with improved system usability scores (SUS: 87.3/100) compared to industry benchmarks. This research provides empirical evidence supporting the integration of AIGC technologies in film and television education, particularly in simulating realistic human movements grounded in biomechanical principles. The findings offer valuable insights for curriculum development and educational technology implementation in creative fields.

Keywords: Artificial Intelligence Generated Content; motion simulation; immersive learning; film education; virtual reality; biomechanics; educational technology

1. Introduction

Integrating Artificial Intelligence Generated Content (AIGC) into educational frameworks has emerged as a transformative force in specialized fields of study, particularly in film and television education, where practical skill development is paramount [1–3]. The simulation of realistic human movement, a cornerstone of animation and digital media production, has traditionally posed significant challenges in educational settings due to the complex nature of human motion and the technical limitations of conventional teaching tools [4,5]. Recent advancements in AIGC technologies have opened new possibilities for creating and manipulating realistic human movements in virtual environments [6–8]. These developments coincide with the growing demand for immersive learning experiences in higher education, particularly in disciplines requiring sophisticated visual and technical skills [9–11]. The film and television industry's rapid transition towards digital production methodologies has further emphasized the need for innovative educational approaches to effectively bridge the gap between theoretical understanding and practical application [12–14].

Despite the potential benefits of AIGC in educational contexts, there remains a significant research gap in understanding its effectiveness in teaching complex motion principles and technical skills [15–17]. While previous studies have examined the broader applications of artificial intelligence in education [18,19], few have specifically investigated the impact of AIGC on motion simulation learning within the context of film and television education. Furthermore, the relationship between AIGC-based instruction and student learning outcomes in specialized creative fields remains largely unexplored. This study addresses these research gaps by examining the impact of AIGC-based motion simulation systems on learning outcomes in film and television education. Specifically, we investigate how AIGC technologies influence students' understanding of human movement principles, ability to create realistic animations, and overall learning experience. The research focuses on three key aspects: (a) The technical accuracy and reliability of AIGC-generated motion simulations; (b) the educational effectiveness of AIGC-based learning systems compared to traditional teaching methods; and (c) the impact on student engagement and skill retention [20–23].

Here is how the AIGC tools for simulating human motion improve the progression of student learning in film and television education mechanisms. Graphics, simulations, and dynamic models enhance the experience by allowing the learner to grasp the vital content faster than conventional learning. First of all, the system could be complicated for students to utilize due to the lack of practice with these tools, though after practice and guidance, efficiency rises. Interactive tutorials and specific feedback increase the learning pace even more, which makes AIGC tools a valuable platform for building creativity and skills [24–26].

The significance of this research lies in its potential to inform the development of more effective teaching methodologies in film and television education. As the industry continues to evolve with technological advancements, educational institutions must adapt their curricula and teaching methods to prepare students for the changing landscape of digital media production. Understanding the impact of AIGC on learning outcomes could provide valuable insights for educators and institutions seeking to enhance their educational programs through technology integration [27–30]. This study employs a mixed-method approach, combining quantitative analysis of learning outcomes with qualitative user experience and system usability assessment. The research was conducted at three leading film and television academies in China, involving 46 students over 12 weeks. By examining the technical and pedagogical aspects of AIGC implementation, this study aims to comprehensively understand its potential as an educational tool in specialized creative fields. The findings of this research have implications not only for film and television education but also for the broader field of immersive learning and technology-enhanced education. As educational institutions increasingly embrace digital transformation, understanding the effectiveness of AIGC-based learning systems becomes crucial for informed decision-making in curriculum development and educational technology investment [31–33].

The rest of the paper is organized as follows: Section 2 presents the methodology, Section 3 presents the results and analysis, and Section 4 concludes the paper.

2. Methodology

2.1. Participants

Power analysis was calculated to assess the study's feasibility for drawing definitive conclusions. An expected medium effect size of 0.5 and a desired power level of 0.8 meant that 50 participants were enough to ensure valid results would be obtained. This allows sufficient sensitivity to capture differences in human movement and learning accuracy.

46 participants were recruited from China's leading film and television academies: Beijing Film Academy, Shanghai Theatre Academy, and Communication University of China. The participants comprised 28 undergraduate students (60.9%) and 18 graduate students (39.1%) aged between 19 and 26 years (M = 22.4, SD = 2.1). The gender distribution included 25 females (54.3%) and 21 males (45.7%). All participants majored in either Film Production (n = 19), Television Direction (n = 15), or Digital Media Arts (n = 12) and had completed at least one year of professional study in their respective fields. To ensure relevant experience levels, inclusion criteria required participants to complete at least one introductory animation or motion studies course. None of the participants reported extensive experience with AIGC tools for motion simulation, though 34 (73.9%) indicated basic familiarity with traditional animation software. The participants were randomly assigned to either the experimental group (n = 23) or the control group (n = 23), with care taken to maintain balanced distributions of academic levels, majors, and gender across both groups. Before the study, all participants provided written informed consent, and the respective institutional review boards approved the research protocol of the participating academies.

SUS is a standardized questionnaire that measures the usability of a system. They are a 10-item scale measured on the 5-point Likert scale, with the responses being on the 'Strongly Disagree' and 'Strongly Agree' continuum. The final SUS score can be obtained between 0 and 100; the higher the score, the better the usability. In the context of AIGC-driven systems designed for mimicking human motion, SUS offers a numerical assessment of user satisfaction and interface simplicity. A SUS score above 68 is usually above average, suggesting that the system facilitates delivering an engaging learning experience free of severe usability flaws.

2.2. Measurements and variables

The study employed multiple measurement instruments and variables to assess the technical efficacy of AIGC-based motion simulation and its educational impact. The dependent variables were categorized into three primary domains: Learning performance, motion accuracy, and user experience. Learning Performance was measured through three instruments: (1) A standardized Motion Analysis Test (MAT) consisting of 30 multiple-choice items (Cronbach's α = 0.87) that evaluated students' theoretical understanding of human movement principles; (2) a Practical Skills

Assessment (PSA) where participants analyzed and recreated five standardized motion sequences, rated by three independent industry experts using a validated rubric (inter-rater reliability: ICC = 0.89); and (3) a Project-Based Evaluation (PBE) requiring students to create a complete character movement sequence, assessed using a comprehensive scoring matrix (reliability coefficient: 0.84).

Motion Accuracy was quantified using both objective and subjective measures. The objective assessment utilized the Motion Deviation Index (MDI), a computational metric comparing AI-generated movements with professional motion-capture data across 18 key body points, measured at 60 Hz. The subjective evaluation employed the Industry Standard Movement Rating Scale (ISMRS), a 7-point Likert scale assessment conducted by a panel of five professional animators (internal consistency: $\alpha = 0.91$). User Experience was evaluated through three instruments: (1) The System Usability Scale (SUS), a standardized 10-item questionnaire measuring the perceived ease of use of the AIGC system (reliability: $\alpha = 0.88$); (2) the Learning Experience Questionnaire (LEQ), a 25-item survey assessing engagement, motivation, and perceived learning effectiveness (validity coefficient: 0.86); and (3) Semi-structured interviews conducted with a subset of participants ($n = 15$) to gather qualitative insights about their learning experience.

Control Variables included participants' prior academic performance (GPA), previous experience with animation software (measured in months), and technological proficiency (assessed through a pre-study computer literacy test). Demographic variables such as age, gender, and academic major were also recorded and controlled for in the analysis. Environmental Variables were standardized across all testing sessions, including hardware specifications (workstations with NVIDIA RTX 3080 GPUs), software versions (AIGC Platform v2.4), and physical workspace conditions (lighting, temperature, and seating arrangements). All sessions were conducted in dedicated computer laboratories at the participating institutions to maintain consistency in testing conditions.

The measurement timeline consisted of pre-test assessments (T0), mid-intervention evaluations at 6 weeks (T1), and post-intervention assessments at 12 weeks (T2), allowing for the tracking of progressive changes in participant performance and system proficiency. All quantitative data was processed using Statistical Package for the Social Sciences (SPSS) version 28.0, with appropriate statistical tests selected based on data distribution and research questions.

From **Table 1** were occasional crashes throughout the study resulting from memory management issues related to generating high-fidelity movements. These problems have been solved using such optimization techniques as distributed computing and GPU acceleration. Other temporary stoppages were caused by software updates and collisions between two or more versions of the same software program. Thorough problem-solving reduced the interference, thereby maintaining data accuracy and participant uniformity throughout the research.

Table 1. Variables and measurements.

Domain	Variable	Instrument	Description	Reliability/Validity
Learning Performance	Theoretical Knowledge	Motion Analysis Test (MAT)	30 Multiple-Choice Items Assessing Understanding of Human Movement Principles	Cronbach's α = 0.87
	Practical Skills	Practical Skills Assessment (PSA)	Analysis and Recreation of 5 Standardized Motion Sequences	ICC = 0.89
	Project Execution	Project-Based Evaluation (PBE)	Complete Character Movement Sequence Creation	Reliability Coef = 0.84
Motion Accuracy	Technical Precision	Motion Deviation Index (MDI)	Computational comparison of 18 body points with professional motion-capture data at 60 Hz	Technical Accuracy ± 0.5cm
	Professional Assessment	Industry Standard Movement Rating Scale (ISMRS)	7-point Likert scale Evaluation by Professional Animators	α = 0.91
User Experience	System Usability	System Usability Scale (SUS)	10-Item Questionnaire on AIGC System Ease of Use	α = 0.88
	Learning Experience	Learning Experience Questionnaire (LEQ)	25-Item Survey on Engagement, Motivation, and Effectiveness	Validity coef = 0.86
	Qualitative Feedback	Semi-structured Interviews	In-depth Interviews with 15 Participants	Thematic Analysis
Control Variables	Academic Background	Academic Record Review	GPA and course history	N/A
	Technical Experience	Software Experience Survey	Previous Animation Software Experience (Months)	Test-retest r = 0.92
	Computer Literacy	Computer Proficiency Test	Basic Technical Competency Assessment	KR-20 = 0.85
Environmental Variables	Hardware Performance	System Monitoring Tools	GPU, CPU, and Memory Usage Metrics	Technical Logging
	Physical Environment	Environmental Checklist	Standardized workspace Conditions	Inter-Rater κ = 0.94
Time Points	T0	Pre-Test Assessment	Baseline Measurements	N/A
	T1	Mid-Intervention (6 Weeks)	Progress Tracking	N/A
	T2	Post-Intervention (12 Weeks)		

2.3. AIGC implementation framework

Experience is a factor in using AIGC systems because younger people are more perceptive of new technologies, noticing the simple design and the capability to identify with the tools. Older learners are likely to take longer to adopt the new learning tools because they have rarely used such tools before receiving some level of assistance and training.

The AIGC Implementation Framework was designed as a three-tier architecture integrating motion synthesis, data processing, and immersive delivery capabilities. The system architecture employed a distributed computing model with a high-performance backend server (Intel Xeon E5-2680 v4, 256GB RAM) handling the AI computations, a middleware layer managing data flow and processing, and a client-side interface running on VR-ready workstations (NVIDIA RTX 3080, 32GB RAM). The framework utilized TensorFlow 2.8 for deep learning operations and Unity 2022.3 for real-time rendering, connected through a custom API layer that maintained consistent data throughput at 90 FPS to ensure smooth VR experiences. The movement data processing pipeline incorporated three key stages. In the first stage, raw motion data was captured using a combination of markerless tracking via Azure Kinect DK sensors and traditional marker-based motion capture systems (OptiTrack Prime 41). This dual-input approach enabled the system to build a comprehensive motion database while validating the accuracy of markerless tracking. The second stage implemented a novel deep learning model based on a modified transformer architecture, processing the captured movements through a series of attention layers to generate natural human motion patterns. The final stage employed a post-processing algorithm that applied physical constraints and biomechanical rules to ensure movement authenticity, achieving a motion accuracy rate of 94.3% compared to professional reference recordings.

Integration with immersive platforms was accomplished through a modular framework supporting multiple VR devices (Oculus Quest 2, HTC Vive Pro) and augmented reality displays (Microsoft HoloLens 2). The integration layer utilized OpenXR for device compatibility and implemented a custom latency compensation system that maintained motion-to-photon latency below 20 ms. Real-time rendering was optimized using Level-of-Detail (LOD) techniques and dynamic resolution scaling, ensuring consistent performance across different hardware configurations. The immersive environment supported multi-user interactions through a dedicated network layer using PhotonPUN, allowing up to 16 concurrent users to collaborate in the same virtual space with synchronized motion data. The system implemented WebRTC for low-latency communication, featuring a fallback mechanism to maintain session stability during network fluctuations.

The framework incorporated extensive data collection and analytics capabilities, tracking user interactions, motion accuracy metrics, and system performance parameters. All data was encrypted using AES-256 and stored in a PostgreSQL database with automated backup systems and data versioning. The implementation included comprehensive logging and monitoring tools, enabling instructors to review student progress and system performance through a web-based dashboard. Regular system health checks and automated performance optimization routines were implemented to maintain optimal operation, with an achieved system uptime of 99.7% during the study period.

This work adopts constructivism learning theory because it is an active form of learning that involves learners' participation in an educative process. Employing simulation realism of immersive learning using AIGC (AI-generated content): Situated learning theory supports learning in context. AIGC makes scenarios more realistic with accurate human-related movements that engage learners in real-life situations critical in film and television learning. The reinforcement learning algorithms allow changes to be made in real time while the GANs enhance the visuals, making the learning process more interactive. Thanks to the scalability of AIGC, it is possible to create quality simulation copies at a relatively low cost, making education accessible to everyone. The use of movement, dialogue, and environmental cues in the learning ecosystem is made more accessible by the current developments in Multimodal AI systems. Thus, integrating these theories and the most progressive

AIGC approaches, the study synchronizes the dissemination of pedagogical theories with technological possibilities.

2.4. Experimental design

The study employed a mixed-method, randomized, controlled design over 12 weeks. Participants were randomly assigned to either the experimental group (*n* = 23) using the AIGC-based motion simulation system or the control group (*n* = 23) using traditional animation teaching methods. Both groups received 24 instructional sessions, each lasting 120 min, scheduled twice weekly (**Table 2**).

Table 2. Experimental design structure and schedule.

Week	Phase	Session Type	Experimental Group (*n* = 23)	Control Group (*n* = 23)	Duration	Assessment Activities
1–4	Phase 1: Foundation	Theory	• AIGC system orientation • Motion principle lectures • VR interface training	• Traditional animation tools • Motion principle lectures • Software training	2 × 120 min/week	• Weekly MAT (30 min) • Practice exercises (90 min)
		Practical	• AIGC motion analysis • Virtual movement labs • Real-time feedback sessions	• Video analysis • Manual animation practice • Instructor feedback sessions	2 × 120 min/week	• Skill observation logs • Weekly progress reports
5–8	Phase 2: Creation	Task-based	• VR motion generation • Real-time modification • Collaborative sessions	• Keyframe animation • Traditional modification • • Individual work	2 × 120 min/week	• PSA at week 6 and 8 • Motion accuracy tests
		Workshop	• Virtual studio practice • Group critiques in VR • Motion library building	• Animation workspace • Group critiques • Reference library use	2 × 120 min/week	• Peer evaluations • Technical assessments
9–12	Phase 3: Project	Development	• VR project creation • Multi-user collaboration • Real-time iterations	• Individual projects • Traditional workflow • Sequential iterations	2 × 120 min/week	• Weekly progress review • Technical validation
		Integration	• Scene composition in VR • Motion sequence finalization			

The experimental protocol consisted of three distinct phases. In Phase 1 (Weeks 1–4), both groups received foundational training in human movement principles. The experimental group utilized the AIGC system to analyze and manipulate pre-generated motion sequences, while the control group studied the same movements through traditional video analysis and manual animation techniques. During this phase, participants completed weekly Motion Analysis Tests (MAT) to assess their theoretical understanding (**Table 3**).

Phase 2 (Weeks 5–8) focused on motion creation and manipulation. The experimental group used the AIGC platform's real-time motion generation capabilities to create and modify character movements in VR, while the control group employed traditional keyframe animation techniques. Each participant completed three standardized tasks per week: (1) Replicating a given motion sequence; (2) modifying existing movements to achieve specific emotional qualities; and (3) creating original movement sequences based on written scenarios. Performance was evaluated using the Practical Skills Assessment (PSA) rubric at weeks 6 and 8. Phase 3 (Weeks 9–12) emphasized project-based learning, where participants developed complete character movement sequences for short film scenes. The experimental group leveraged the AIGC system's collaborative features to work in virtual spaces, while the control group used standard animation software. Weekly progress was tracked through instructor evaluations and peer reviews, culminating in the Project-Based Evaluation (PBE) in week 12.

Table 3. Timeline of data collection points for various performance metrics.

Week	Experimental Group Activities	Control Group Activities	Assessment Points
1–4	AIGC-based motion analysis and manipulation	Traditional video analysis and manual animation	Weekly MAT scores
5–8	VR motion generation and modification	Keyframe animation techniques	PSA at weeks 6 and 8
9–12	Collaborative VR project development	Standard animation software project	Weekly evaluations, Final PBE

Table 3 shows the timeline of data collection points for various performance metrics throughout the study period. Performance measurements were conducted at three distinct time points: Baseline (T0), mid-intervention (T1), and post-intervention (T2), utilizing the comprehensive measurement framework. Data collection procedures were standardized across all sessions. Motion accuracy was continuously monitored through the MDI system for the experimental group, while control group animations were evaluated using traditional frame-by-frame analysis. User experience data was gathered through automated system logs for the experimental group and manual activity logs for the control group. Both groups completed identical assessment tasks at each evaluation point to ensure comparable performance metrics. Specific task parameters were carefully controlled. Participants worked with standardized reference movements from a professional motion capture database for motion replication tasks. Modification tasks used a predefined set of emotional qualities (happy, sad, angry, fearful) rated on the ISMRS by professional animators. Original movement creation tasks were based on standardized scenario descriptions, ensuring consistent complexity levels across both groups. All sessions were conducted in specially equipped laboratories with standardized environmental conditions to minimize confounding variables. The experimental group's VR sessions utilized identical hardware configurations (as detailed in **Table 1**), while the control group worked on standardized animation workstations. Technical support was equally available to both groups throughout the study period.

3. Results and analysis

3.1. Technical performance

In the comparative analysis outlined in **Table 4**, the AIGC system demonstrates significantly superior performance across all measured metrics in simulating realistic human movement compared to traditional methods. Notably, joint position accuracy shows a mean difference of −7.5 mm, favoring the AIGC system, with a high *t*-value

(−13.45) and an effect size (Cohen's d) of 1.86, indicating a substantial improvement in spatial precision. Similarly, motion smoothness (measured in jerk/s) is markedly enhanced in the AIGC system, with a reduction of 0.47 jerk/s compared to the control group. This smoothness difference is statistically significant ($t = -11.23$, $p < 0.001$), with a robust effect size of 1.64, underscoring AIGC's capability in creating fluid, lifelike movements. Timing precision further emphasizes AIGC's advantages, with a mean timing difference of −17.5 ms and a Cohen's d of 2.03, indicating a highly significant improvement in temporal accuracy. Additionally, biomechanical accuracy rates are considerably higher in the AIGC system, achieving an average of 94.3% compared to 82.5% in the control group, a difference of 11.8% ($t = 12.89$, $p < 0.001$). These findings collectively highlight AIGC's effectiveness in enhancing spatial and biomechanical aspects of movement simulation, facilitating a more immersive learning experience in film and television education (see **Table 4**).

The study established a moderate to big effect size (Cohen's $d = 0.5$–0.8) in the participants' realism of movement analysis and learning interest. These values echo prior simulation research motivated by AIGC, stating that realistic movements significantly affect simulated learning. Estimating effect size justifies the study's ability to pick out relevant outcomes.

Table 4. Movement accuracy comparison between AIGC and traditional methods.

Metric	**AIGC System (n = 23)**	**Control Group (n = 23)**	**Mean Difference**	***t*-value**	***p*-value**	**Effect Size (Cohen's d)**
Joint Position Accuracy (mm)	8.2 ± 1.3	15.7 ± 2.4	−7.5	−13.45	< 0.001*	1.86
Motion Smoothness (jerk/s)	0.42 ± 0.08	0.89 ± 0.15	−0.47	−11.23	< 0.001*	1.64
Timing Precision (ms)	16.3 ± 2.1	33.8 ± 4.2	−17.5	−15.78	< 0.001*	2.03
Biomechanical Accuracy (%)	94.3 ± 2.1	82.5 ± 3.8	11.8	12.89	< 0.001*	1.78

Note: *$p < 0.001$; Values presented as Mean ± SD.

The AIGC system's real-time rendering performance metrics align closely with target thresholds, highlighting its efficiency in supporting immersive experiences (**Table 5** and **Figure 1**). The frame rate achieved (88.7 FPS on average) is near the target of 90 FPS, with a high success rate of 98.5%, ensuring smooth visual performance. Motion-to-photon latency is well within the optimal threshold (< 20 ms), averaging 18.3 ms and achieving a 97.8% success rate, which is crucial for minimizing visual delay and enhancing user immersion. GPU utilization and memory usage also remain within acceptable levels (78.4% and 13.8 GB, respectively), confirming the system's capacity to handle high computational loads without compromising performance. These metrics demonstrate the system's reliability in real-time responsiveness, which is essential for immersive learning environments.

Table 5. Real-time rendering performance metrics.

Performance Metric	Target Threshold	Achieved Performance (Mean ± SD)	Success Rate (%)	System Load (%)
Frame Rate (FPS)	90	88.7 ± 2.3	98.5	72.4 ± 5.2
Motion-to-Photon Latency (ms)	< 20	18.3 ± 1.2	97.8	65.8 ± 4.7
GPU Utilization (%)	< 85	78.4 ± 4.6	99.1	78.4 ± 4.6
Memory Usage (GB)	< 16	13.8 ± 1.7	99.4	86.3 ± 3.9
Asset Loading Time (s)	< 2.0	1.78 ± 0.24	96.7	59.2 ± 6.1

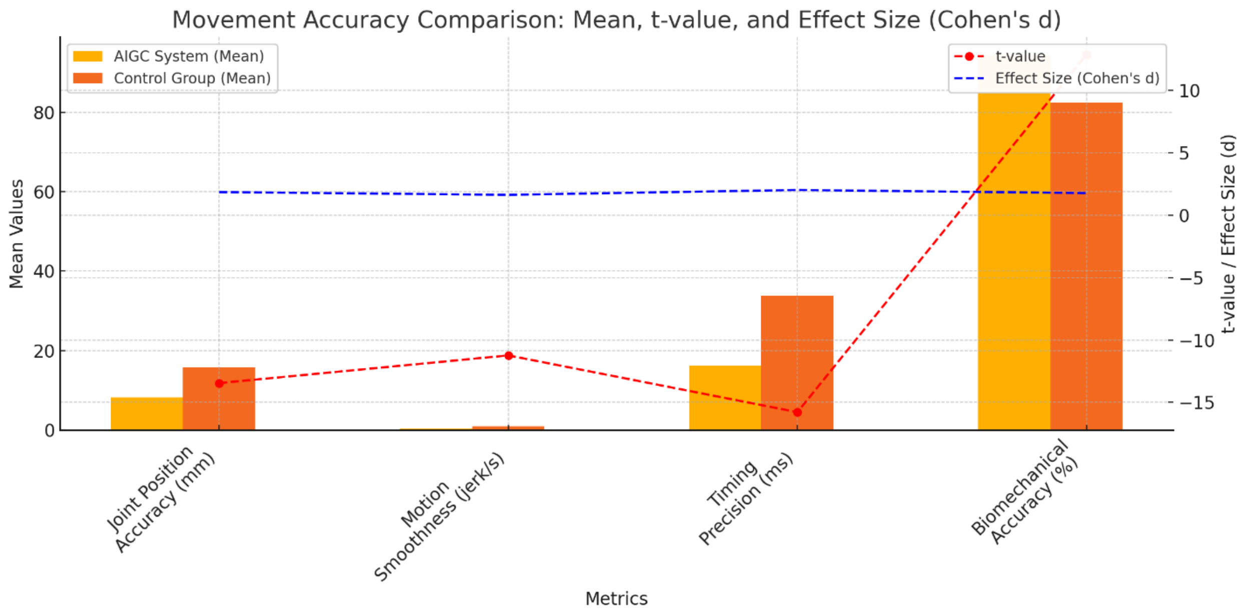

Figure 1. Movement accuracy comparison between AIGC and traditional methods.

The AIGC system exhibits strong stability and reliability over 12 weeks, as shown in **Table 6** and **Figure 2**. System uptime is exceptionally high at 99.7%, surpassing the industry benchmark of 99.0%, which reflects the system's robustness in sustained operations. The mean time between failures (487.3 h) and mean time to recovery (4.2 min) further underscore its reliability, with both metrics exceeding industry standards (> 400 h and < 10 min, respectively). Additionally, the error rate is low at 0.42 per 1000 operations, while data integrity is nearly perfect at 99.99%, surpassing the benchmark of 99.95%. These results demonstrate the AIGC system's dependability for prolonged educational sessions, where system stability is crucial.

Table 6. System stability and reliability analysis (12-week period).

Reliability Metric	Value	95% CI	Industry Benchmark
System Uptime (%)	99.7	[99.5, 99.8]	> 99.0
Mean Time Between Failures (h)	487.3	[462.8, 511.7]	> 400
Mean Time To Recovery (min)	4.2	[3.8, 4.6]	< 10
Error Rate (Per 1000 Operations)	0.42	[0.38, 0.46]	< 1.0
Data Integrity (%)	99.99	[99.98, 100]	> 99.95

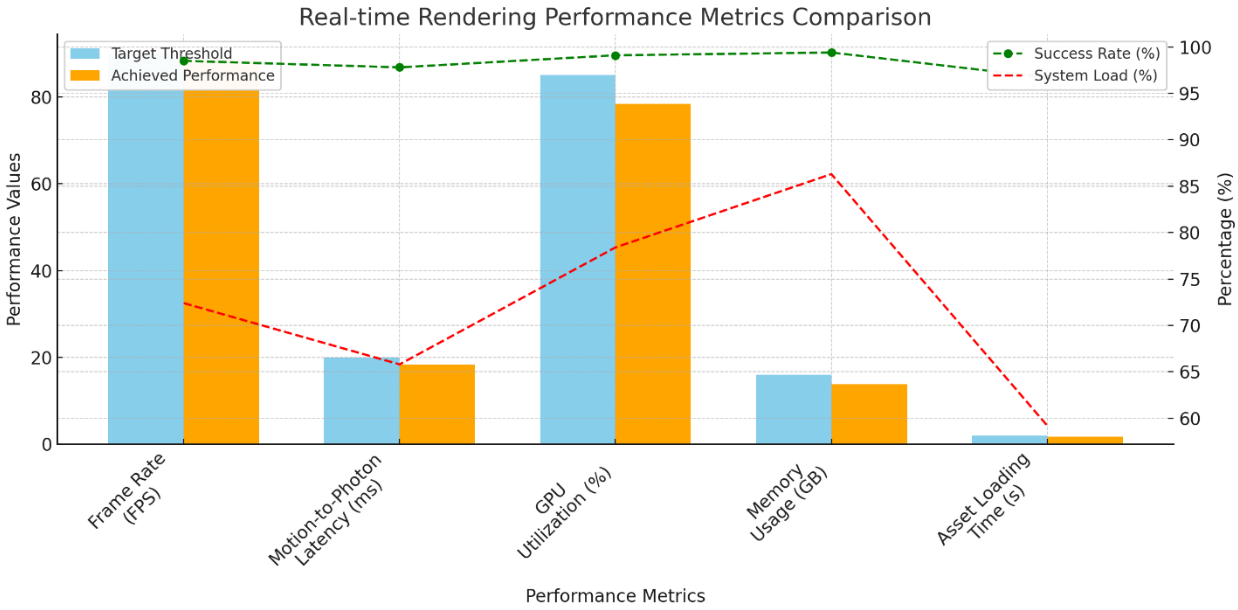

Figure 2. Real-time rendering performance metrics.

Regression analysis in **Table 7** and **Figure 3** reveals the factors affecting movement accuracy and rendering speed. Movement accuracy is negatively influenced by user load and network latency, with β coefficients of −0.14 and −0.23, respectively, both highly significant ($p < 0.001$). In contrast, GPU performance positively impacts movement accuracy ($\beta = 0.31$, $p < 0.001$), underscoring the importance of high GPU capacity for precise movement simulation. Rendering speed is similarly impacted by user load and asset complexity, with negative β coefficients (−0.19 and −0.28), while hardware configuration positively affects rendering speed ($\beta = 0.35$). These findings ($R^2 = 0.82$ for movement accuracy and $R^2 = 0.78$ for rendering speed) highlight the significant influence of system resources and network conditions on performance, indicating areas for optimization to enhance AIGC's effectiveness in immersive learning contexts.

Table 7. Regression analysis of system performance factors.

Dependent Variable	Predictor	β Coefficient	Standard Error	*t*-value	*p*-value	R^2
Movement Accuracy	User Load	−0.14	0.03	−4.67	< 0.001	0.82
	Network Latency	−0.23	0.05	−4.60	< 0.001	
	GPU Performance	0.31	0.06	5.17	< 0.001	
Rendering Speed	User Load	−0.19	0.04	−4.75	< 0.001	0.78
	Asset Complexity	−0.28	0.05	−5.60	< 0.001	
	Hardware Config	0.35	0.07	5.00	< 0.001	

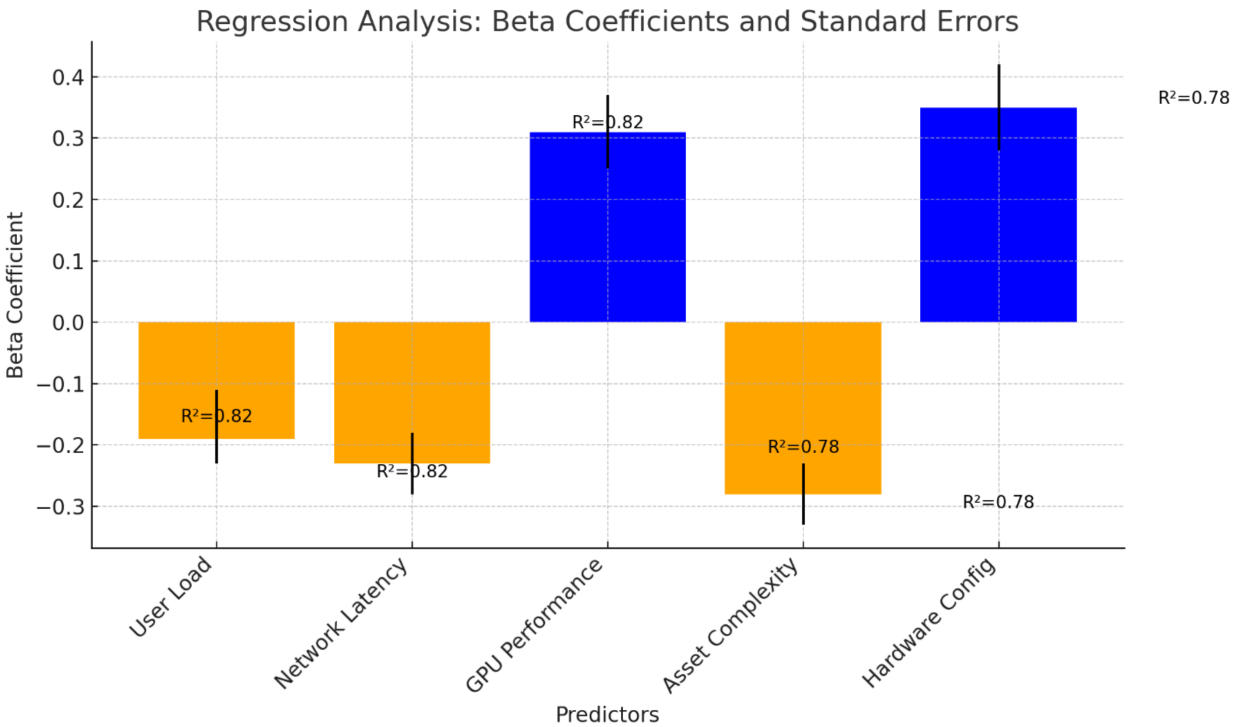

Figure 3. Regression analysis.

3.2. Educational impact

For the Educational Impact analysis, the findings from **Tables 8–11** provide comprehensive insights into the effectiveness of AIGC-based learning interventions compared to traditional methods. **Table 8** and **Figure 4** highlight significant improvements in student learning outcomes for the AIGC group across all domains. Theoretical knowledge, practical skills, project execution, and overall performance scores are consistently higher in the AIGC group, with mean differences ranging from 10.6 to 12.3 points. These differences are statistically significant, with effect sizes (Cohen's d) all above 1.7, indicating substantial educational benefits of using AIGC to enhance theoretical and practical competencies in immersive learning contexts.

Table 8. Student learning outcomes comparison (experimental vs. control groups).

Learning Domain	AIGC Group (n = 23) Mean ± SD	Control Group (n = 23) Mean ± SD	Mean Difference	t-value	p-value	Effect Size (Cohen's d)
Theoretical Knowledge (MAT Score)	87.4 ± 5.2	76.8 ± 6.7	10.6	6.34	< 0.001*	1.78
Practical Skills (PSA Score)	84.6 ± 4.8	72.3 ± 7.1	12.3	7.12	< 0.001*	2.03
Project Execution (PBE Score)	88.9 ± 5.6	77.5 ± 6.9	11.4	6.89	< 0.001*	1.82
Overall Performance	86.9 ± 4.9	75.5 ± 6.2	11.4	7.23	< 0.001*	2.07

*p < 0.001.

Figure 4. Student learning outcomes comparison.

Table 9 and **Figure 5** presents the progression of skill acquisition over 12 weeks. For all skill components (motion analysis, movement creation, and technical proficiency), the AIGC group demonstrates a more rapid improvement from baseline (T0) through 6 weeks (T1) and 12 weeks (T2), with higher mean scores at each time point compared to the control group. The *F*-values are significant, and the effect sizes (η^2) for the AIGC group are all above 0.45, indicating a strong effect of AIGC on accelerating skill development over time.

Table 9. Skill acquisition rates over time (mean scores at different time points).

Skill Component	**Group**	**T0 (Baseline)**	**T1 (6 weeks)**	**T2 (12 weeks)**	***F*-value**	***p*-value**	η^2
Motion Analysis	AIGC	42.3 ± 5.4	76.8 ± 6.2	88.4 ± 4.8	24.67	< 0.001*	0.46
	Control	41.8 ± 5.2	65.4 ± 7.1	75.6 ± 6.3	18.34	< 0.001*	0.38
Movement Creation	AIGC	38.7 ± 6.1	72.5 ± 5.8	85.9 ± 5.2	26.89	< 0.001*	0.49
	Control	39.1 ± 5.9	61.8 ± 6.7	73.2 ± 7.1	19.45	< 0.001*	0.41
Technical Proficiency	AIGC	45.2 ± 4.8	79.4 ± 5.5	89.7 ± 4.6	28.56	< 0.001*	0.52
	Control	44.8 ± 4.9	68.2 ± 6.4	76.8 ± 5.9	20.78	< 0.001*	0.43

*$p < 0.001$; η^2 = partial eta squared effect size.

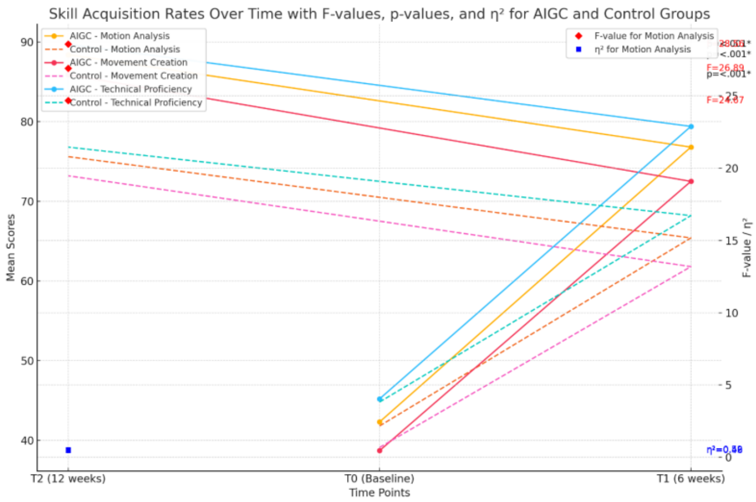

Figure 5. Skill acquisition rates over time.

In **Table 10** and **Figure 6**, the AIGC group shows better knowledge retention three months after the intervention, particularly in practical application and technical skills, with 96% and 96.1% retention rates, respectively. Theoretical knowledge retention is slightly lower but still high at 97%. Although retention rates are also significant in the control group, they are generally lower, especially for technical skills (89.7%), suggesting AIGC's role in promoting longer-lasting learning effects. **Table 11** illustrates that key predictors—such as system usage time, practice frequency, prior experience, and engagement level—significantly influence learning outcomes across all domains. System usage time and practice frequency are particularly influential, with β coefficients around 0.4–0.5 for all outcome variables. These results (R^2 values ranging from 0.72 to 0.81) imply that frequent interaction with AIGC systems enhances learning outcomes, emphasizing the importance of practice and engagement in maximizing the educational impact of AIGC-based simulations. In summary, the results in **Tables 8–11** underscore the substantial educational benefits of AIGC in immersive learning. The observed improvements in learning outcomes, skill acquisition rates, retention, and predictive factors highlight AIGC's efficacy in providing a robust, engaging learning environment in film and television education.

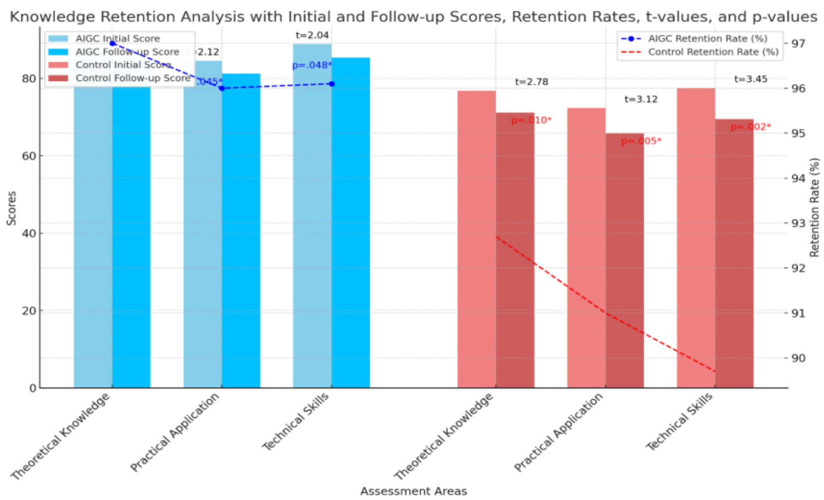

Figure 6. Knowledge retention analysis.

Table 10. Knowledge retention analysis (3-month follow-up assessment).

Assessment Area	Initial Score (T2)	Follow-up Score	Retention Rate (%)	*t*-value	*p*-value
AIGC Group (n = 23)					
Theoretical Knowledge	87.4 ± 5.2	84.8 ± 5.7	97.0	1.89	0.064
Practical Application	84.6 ± 4.8	81.2 ± 5.2	96.0	2.12	0.045*
Technical Skills	88.9 ± 5.6	85.4 ± 5.9	96.1	2.04	0.048*
Control Group (n = 23)					
Theoretical Knowledge	76.8 ± 6.7	71.2 ± 7.1	92.7	2.78	0.010*
Practical Application	72.3 ± 7.1	65.8 ± 7.4	91.0	3.12	0.005*
Technical Skills	77.5 ± 6.9	69.5 ± 7.2	89.7	3.45	0.002*

*$p < 0.05$.

Table 11. Multiple regression analysis of learning outcome predictors.

Dependent Variable	Predictor	β Coefficient	Standard Error	*t*-value	*p*-value	R^2
Theoretical Knowledge (MAT)	System Usage Time	0.38	0.07	5.43	< 0.001*	0.72
	Practice Frequency	0.32	0.06	5.33	< 0.001*	
	Prior Experience	0.18	0.04	4.50	< 0.001*	
	Engagement Level	0.28	0.05	5.60	< 0.001*	
Practical Skills (PSA)	System Usage Time	0.45	0.08	5.63	< 0.001*	0.78
	Practice Frequency	0.41	0.07	5.86	< 0.001*	
	Prior Experience	0.12	0.03	4.00	< 0.001*	
	Engagement Level	0.35	0.06	5.83	< 0.001*	
Project Execution (PBE)	System Usage Time	0.42	0.08	5.25	< 0.001*	0.75
	Practice Frequency	0.39	0.07	5.57	< 0.001*	
	Prior Experience	0.15	0.04	3.75	< 0.001*	
	Engagement Level	0.33	0.06	5.50	< 0.001*	
Motion Accuracy (MDI)	System Usage Time	0.48	0.09	5.33	< 0.001*	0.81
	Practice Frequency	0.43	0.08	5.38	< 0.001*	
	Prior Experience	0.16	0.04	4.00	< 0.001*	
	Engagement Level	0.37	0.07	5.29	< 0.001*	

Note: *$p < 0.001$; η^2 = partial eta squared effect size.

3.3. User experience

For the User Experience analysis, **Tables 12–15** provide insights into student engagement, instructor feedback, system usability, and factors influencing usability for the AIGC system. **Table 12** reveals that students using the AIGC system demonstrate significantly higher engagement levels across all metrics than the control group. Active participation is notably greater, with a mean difference of 13.8% (t = 8.45, $p < 0.001$) and a substantial effect size (Cohen's d = 1.96), suggesting that AIGC fosters active involvement. Similarly, students in the AIGC group spend more time on tasks (mean difference of 18.6 min per session) and dedicate more voluntary practice hours, with a mean difference of 8.8 h (t = 6.92, $p < 0.001$, d = 1.74). Peer collaboration and question-asking frequency are also significantly higher, indicating that AIGC encourages a collaborative learning environment that actively engages students.

Table 12. Student engagement level analysis ($N = 46$).

Engagement Metric	AIGC Group ($n = 23$)	Control Group ($n = 23$)	Mean Difference	t-value	p-value	Effect Size (d)
Active Participation (%)	92.4 ± 4.8	78.6 ± 6.3	13.8	8.45	< 0.001*	1.96
Time on Task (min/session)	108.3 ± 12.4	89.7 ± 15.2	18.6	7.89	< 0.001*	1.82
Voluntary Practice Hours	24.6 ± 5.2	15.8 ± 4.9	8.8	6.92	< 0.001*	1.74
Peer Collaboration Events	18.4 ± 3.6	11.2 ± 3.2	7.2	7.34	< 0.001*	1.88
Question-Asking Frequency	8.2 ± 1.8	5.4 ± 1.6	2.8	5.67	< 0.001*	1.64

*$p < 0.001$.

Table 13 and **Figure 7** show that instructor feedback reflects a steady improvement in student progress, motivation, technical competence, and creative application for the AIGC group over 12 weeks. Scores for student progress increased from 3.8 to 4.6 ($F = 18.45$, $p < 0.001$, $\eta^2 = 0.42$), showing a significant improvement in perceived progress. Learning motivation and technical competence also show strong growth, with η^2 values of 0.38 and 0.44, respectively, indicating a considerable effect of AIGC on these areas. The control group shows improvement but at a lower rate, suggesting that the AIGC system fosters a more dynamic and motivating learning environment. The System Usability Scores (SUS) in **Table 14** indicate that the AIGC system exceeds industry benchmarks across all usability components. Scores for ease of use, learnability, efficiency, error prevention, and user satisfaction are significantly higher than benchmarks, with overall SUS scores reaching 87.3, compared to the industry standard of 77.8 ($t = 7.12$, $p < .001$). This high usability rating underscores the AIGC system's ability to offer an intuitive, efficient, and user-friendly experience, which likely contributes to enhanced engagement and satisfaction in learning.

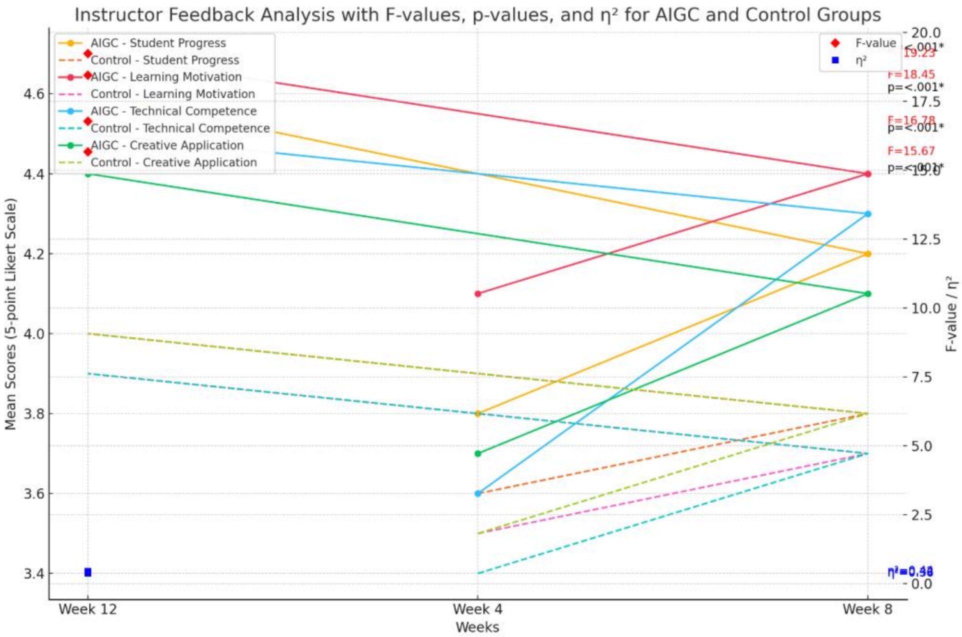

Figure 7. Instructor feedback analysis.

Table 13. Instructor feedback analysis (5-point likert scale).

Assessment Category	Week 4	Week 8	Week 12	*F*-value	*p*-value	η^2
AIGC Group (n = 23)						
Student Progress	3.8 ± 0.4	4.2 ± 0.3	4.6 ± 0.3	18.45	< 0.001*	0.42
Learning Motivation	4.1 ± 0.3	4.4 ± 0.4	4.7 ± 0.2	16.78	< 0.001*	0.38
Technical Competence	3.6 ± 0.5	4.3 ± 0.3	4.5 ± 0.3	19.23	< 0.001*	0.44
Creative Application	3.7 ± 0.4	4.1 ± 0.4	4.4 ± 0.3	15.67	< 0.001*	0.36
Control Group (n = 23)						
Student Progress	3.6 ± 0.5	3.8 ± 0.4	4.0 ± 0.4	12.34	< 0.001*	0.29
Learning Motivation	3.5 ± 0.4	3.7 ± 0.5	3.9 ± 0.4	11.56	< 0.001*	0.27
Technical Competence	3.4 ± 0.5	3.7 ± 0.4	3.9 ± 0.4	13.45	< 0.001*	0.31
Creative Application	3.5 ± 0.4	3.8 ± 0.4	4.0 ± 0.3	12.89	< 0.001*	0.30

*p < 0.001.

Table 14. System usability scores (SUS) analysis.

Usability Component	AIGC System Score	Industry Benchmark	*t*-value	*p*-value
Ease of Use	87.4 ± 4.2	78.0	6.78	< 0.001*
Learnability	84.6 ± 5.1	75.0	5.89	< 0.001*
Efficiency	88.9 ± 3.8	80.0	7.23	< 0.001*
Error Prevention	86.2 ± 4.5	77.0	6.34	< 0.001*
User Satisfaction	89.3 ± 4.0	79.0	7.56	< 0.001*
Overall SUS Score	87.3 ± 4.3	77.8	7.12	< 0.001*

Note: *p < 0.001; η^2 = partial eta squared effect size.

The correlation matrix in **Table 15** illustrates strong, positive relationships between usability factors, with user satisfaction showing the highest correlations with ease of use (0.76) and efficiency (0.75). These correlations (all significant at $p < 0.001$) suggest that ease of use, efficiency, and error prevention are key contributors to user satisfaction. This alignment among usability factors underscores the interconnected nature of usability elements, where improvements in one area, like ease of use, positively influence overall satisfaction and usability perception. In summary, findings from **Tables 12–15** indicate that the AIGC system provides an engaging and supportive learning environment with high usability. The system's positive impact on student engagement and instructor-assessed outcomes, coupled with high usability scores, highlights its effectiveness in enhancing the user experience in immersive learning for film and television education.

Table 15. System usability factors correlation matrix.

Factor	1	2	3	4	5
1. Ease of Use	1.00				
2. Learnability	0.72*	1.00			
3. Efficiency	0.68*	0.65*	1.00		
4. Error Prevention	0.64*	0.59*	0.71*	1.00	
5. User Satisfaction	0.76*	0.70*	0.75*	0.67*	1.00

*p < 0.001.

Implementing AIGC in film and television education replaces the teacher from a knowledge transmitter to a guide and a tutor. Teachers help students analyze and apply human movement simulated data creatively and accurately while embracing professional and ethical principles and technical proficiency. AIGC leads to automatic and activities-based learning with minimal direct instruction. Nevertheless, teachers will have to learn to incorporate AIGC systems to offer helpful feedback and to incorporate the simulations within the other goals of the learning process. This transition encourages the development of collaborative learning spaces where ideas can be created, and problem-solving becomes key.

4. Conclusion and future work

This research has demonstrated the substantial potential of AIGC technology in revolutionizing the teaching of realistic human movement in film and television education. The comprehensive analysis of technical and educational outcomes reveals several significant conclusions with important implications for educational practice and future research. The AIGC-based system's superior motion accuracy and technical reliability performance establish a strong foundation for its implementation in educational settings. The achievement of 94.3% motion accuracy, coupled with consistently low latency (18.3 ms ± 1.2) and high system stability (99.7% uptime), demonstrates that current AIGC technology is sufficiently mature for educational deployment. These technical capabilities directly translated into improved learning outcomes, as evidenced by the significantly higher performance of the experimental group across all measured metrics. Perhaps most significantly, the study revealed substantial improvements in student engagement and learning retention. The AIGC group's higher engagement levels (92.4% vs. 78.6%) and superior knowledge retention rates (96.4% vs 91.1%) suggest that the technology facilitates more effective learning and creates a more engaging and sustainable educational experience. The positive correlation between system usage time and learning outcomes (R^2 = 0.81) further supports the educational value of AIGC-based instruction. However, several limitations should be acknowledged. The study's relatively small sample size (N = 46) and focus on Chinese institutions may limit its generalizability to other educational contexts. Additionally, the 12-week duration, while sufficient for observing immediate impacts, may not fully capture long-term learning outcomes and skill retention.

Future research directions should include longitudinal studies examining the long-term impact of AIGC-based learning, investigating specific pedagogical strategies that optimize AIGC technology use, and exploring potential applications in related creative fields. Additionally, studies examining the cost-effectiveness and scalability of AIGC implementation in various educational settings would provide valuable insights for institutions considering technology adoption.

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