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Article

A biomechanics-oriented study on the impact of AIGC on user interaction and ergonomics in visual communication design

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Abstract: This study investigates the biomechanical implications and ergonomic impacts of AI-generated content (AIGC) integration in visual communication design workflows. Through a comprehensive analysis of 23 professional designers in Chengdu, China, we examined the physical stress patterns, user interaction dynamics, and overall ergonomic outcomes when transitioning from traditional to AIGC-assisted design processes. The research employed a mixed-method approach combining quantitative biomechanical measurements with qualitative user experience assessments over 12 weeks. Results revealed significant reductions in muscle activity across key muscle groups, with the upper trapezius showing the most significant decrease (−3.6% MVC, $p < 0.001$) during AIGC-assisted tasks. This change in muscle activity can be further linked to alterations in the body's postural stability and load distribution, which are core considerations in biomechanics. Movement efficiency metrics, which are inherently related to biomechanical performance, demonstrated a 27.9% reduction in task completion time ($p < 0.001$) and a 33.3% decrease in design iterations. Quality assessment scores improved across all dimensions, with Creative Innovation showing the highest enhancement (+1.8 points, $p < 0.001$). User satisfaction metrics indicated significant improvements, with consistent gains of 1.1 points (on a 5-point scale) across all measured dimensions ($p < 0.001$). Notably, the study identified distinct adaptation patterns between novice and experienced users in terms of their biomechanical responses. Experienced users demonstrated significantly faster response times in AIGC prompt input (8.94 ± 1.87 s vs 18.62 ± 3.15 s, $p < 0.001$), which can be associated with differences in their neuromuscular coordination and motor learning abilities. While AIGC integration initially increased certain types of errors (+51.2% in input errors), it led to substantial reductions in tool misuse (−40.4%) and design revisions (−39.9%). These findings suggest that AIGC integration can significantly reduce physical stress while improving design efficiency and quality outcomes, all of which are intertwined with the biomechanical functioning of the body during the design process. The research provides evidence-based recommendations for optimizing AIGC implementation in professional design workflows, taking into account the biomechanical and ergonomic factors that contribute to the overall well-being and creative productivity. This study has important implications for software development, workplace health policies, and the future direction of AI-assisted creative work, as it highlights the significance of considering biomechanics in the integration of advanced technologies within creative domains.

Keywords: AIGC; visual communication design; biomechanics; ergonomics; user interaction; design workflow; AI integration; professional design practice

1. Introduction

The rapid evolution of artificial intelligence and its integration into creative processes has fundamentally transformed the landscape of visual communication design [1–3]. As we navigate through the third decade of the 21st century, AI-generated content (AIGC) has emerged as a pivotal force reshaping traditional design workflows, challenging established ergonomic paradigms, and redefining user interaction patterns in professional design practices [4–6]. Visual communication design has traditionally been characterized by intensive human-computer interaction, requiring prolonged focused attention, precise motor control, and complex cognitive processing [7,8]. These tasks' physical and cognitive demands have long been associated with various occupational health concerns, including musculoskeletal disorders, visual strain, and cognitive fatigue [9,10]. The emergence of AIGC technologies presents opportunities and challenges in addressing these ergonomic concerns while potentially transforming the fundamental nature of design work [11–13].

Recent advancements in generative AI, particularly in areas such as image synthesis, layout generation, and style transfer, have introduced new tools and workflows that significantly differ from traditional design software interactions [14,15]. These developments have created an urgent need to understand how AIGC integration affects the biomechanical loads, interaction patterns, and overall ergonomic well-being of design professionals [16]. Previous studies have primarily focused on either the creative capabilities of AI tools or traditional ergonomic assessments of design work, leaving a critical gap in understanding the biomechanical implications of AIGC integration [17–20].

This study aims to comprehensively investigate the biomechanical impact of AIGC integration in visual communication design through the following objectives:

(a) To quantify and compare the biomechanical loads experienced during traditional and AIGC-assisted design tasks through detailed motion analysis and muscle activation measurements.

(b) To analyze changes in user interaction patterns and their relationship to physical stress and fatigue development when incorporating AIGC tools into established design workflows.

(c) To evaluate the effectiveness of AIGC integration in reducing ergonomic risk factors while maintaining or improving design quality and efficiency.

(d) To develop evidence-based recommendations for optimal AIGC integration that promotes both ergonomic well-being and design effectiveness.

The significance of this research extends across theoretical, practical, and industry dimensions. From a theoretical perspective, this study contributes to the emerging field of human-AI interaction ergonomics, providing quantitative insights into how AI assistance affects human biomechanics during creative tasks. The findings fill a crucial gap in understanding the physical implications of AI integration in professional creative work [21–25]. Practically, this research offers valuable insights for software developers, ergonomists, and design professionals. By identifying specific biomechanical patterns and risk factors associated with AIGC use, the study informs the development of more ergonomically sound AI tools and integration strategies. The results provide evidence for developing workplace guidelines that optimize the balance between AI assistance and human well-being [26–33].

Human-machine collaboration in creative fields is done out of a desire to combine human instincts with the result-optimizing powers of artificial intelligence. It is noted that designers apply AI for conceptual creation, creating something new and unique or for making some routine work done, but the design process remains with the designers. Composers use AI algorithm for creating responsive original scores, fusing styles, or creating sonic backgrounds. This is where the AI comes into play, it is used by filmmakers for realistic CGI or script analysis. Still, the ethical questions, copyright questions, and the desire to stay creative prevent this from happening. Collaborative systems involve the use of user interfaces and therefore should have a good stable user interface and training. Also, the advocacy that AI provides in improving accessibility increases an array of opportunities in creative industries for individuals with varied ability. That sort of partnership reimagines the nature of innovation, as well as the combination of human insight with computing accuracy.

This research arrives at a critical juncture for the design industry as organizations increasingly adopt AI tools. The findings help inform decision-making around AIGC implementation, training protocols, and workplace health and safety policies. Understanding the biomechanical implications of AIGC integration is essential for maintaining workforce health while maximizing the benefits of AI technology. This study also addresses broader societal concerns about the impact of AI on professional work, providing empirical evidence of how AI integration affects the physical demands of creative labor. As AIGC tools become more prevalent, insights from this research will be crucial in shaping policies and practices that ensure sustainable and healthy integration of AI in creative professions.

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

2. Methodology

Machine learning applications widely known as artificial intelligence generated content (AIGC) involves using of advanced AI techniques such as deep learning and generative models. MidJourney and DALL-E, Runway are some of the models based on generative adversarial networks (GANs) and transformer models that generate good quality images, videos or text. These tools enable the designer to type in prompts or other reference materials, the design concepts can be developed, styles copied or visuals enhanced quickly. AIGC tools also support natural language processing (NLP) for easy communication, cutting down cycle time involved in concepting, and minimizing the workload. In doing so they free up time for strategic creativity and ideation, and fundamentally altering the vector of user engagement in visual communication design.

2.1. Participants

This study recruited 23 participants from Chengdu, Sichuan Province, China. The sample consisted of 13 Females (56.5%) and 10 Males (43.5%), with ages ranging from 24 to 45 years ($M = 32.4$, $SD = 5.8$). All participants had normal or corrected-to-normal vision and reported no history of musculoskeletal disorders or neurological conditions that could affect their interaction with digital interfaces. The participants represented diverse professional backgrounds in visual communication design: 8 were professional designers with more than five years of experience, 7 were junior designers with 1–4 years of experience, 5 were design educators, and 3 were graduate students in visual communication programs. The average professional experience in design-related fields was 6.3 years (SD = 3.2). Selection criteria included: (1) minimum one year of professional experience in visual design or related fields, (2) familiarity with at least one AI-powered design tool, (3) no pre-existing physical conditions that might affect biomechanical measurements, and (4) availability for all three phases of the study. Participants were recruited through local design associations, universities, and professional networks in Chengdu. Before participation, all subjects provided written informed consent following protocols approved by the University Ethics Committee. Participants were compensated with 200 RMB for their time and involvement in the study. To ensure participant privacy, each subject was assigned a unique identifier (P01–P23) used throughout data collection and analysis.

2.2. Research design

This study employed a mixed-method research design, integrating quantitative biomechanical measurements with qualitative user experience assessments to comprehensively evaluate the impact of AIGC on visual communication design workflows. The research was conducted over 12 weeks from September to December 2023.

Based on the results, it is recommended that designers integrate AIGC tools in VCD through iterative design processes that alternate between AI and design creativity. There must be refresher courses on how to write effective prompts and on the functions of the tools. Solutions with comfortable designs that are easy to learn and engage with AI should be given the highest value to prevent physical and mental stress. It is suggested that in institutions, AIGC modules should be included in the course of design for future professionals. It has been found that synergistic interaction between developers and designers can make AI tools more focused for specific usages. Lastly, the promotion of ethical principles maintains the originality of designs, which in turn creates confidence in AIGC-created work as the appropriate use of such tools allows the professionals to effectively and sustainably incorporate them.

i) Mixed-method approach: The study utilized a concurrent triangulation design where quantitative and qualitative data were collected simultaneously. The quantitative phase focused on capturing biomechanical measurements using motion capture technology, eye-tracking data, performance metrics tracking, and physiological measurements, including muscle tension and posture analysis. Simultaneously, the qualitative phase involved semi-structured interviews, think-aloud protocols during task execution, observational field notes, and post-task reflection sessions. These two data streams were then integrated through cross-validation and pattern matching to understand the user experience concerning biomechanical data comprehensively.

ii) Data collection instruments: The biomechanical assessment utilized the Vicon Motion Capture System (Vicon Nexus 2.12) with 8 infrared cameras for precise movement tracking. Surface EMG sensors (Delsys Trigno™) were employed to monitor muscle activity, while a Tobii Pro Spectrum eye tracker operating at 300 Hz captured detailed gaze patterns. Digital RULA/REBA tools were implemented for ergonomic assessment to evaluate postural risks. User experience was assessed through custom-designed task analysis forms, complemented by standardized tools, including the NASA Task Load Index (TLX) for cognitive load assessment and the System Usability Scale (SUS) questionnaire. Semi-structured interviews following a 15-question core protocol provided more profound insights into user perspectives. Performance monitoring incorporated screen recording software (Camtasia Studio 2023) alongside custom-developed time-tracking and error-logging systems.

iii) Sampling strategy: The study implemented a purposive sampling approach with stratified elements to ensure comprehensive representation across expertise levels and professional backgrounds. An initial pool was created through database compilation from local design associations, professional network outreach, academic institution partnerships, and targeted social media announcements in relevant professional groups. The stratification process considered professional experience categories (junior: 1–4 years, senior: 5 + years), AIGC tool familiarity levels, design specialization areas, and age groups. Selection proceeded through a systematic process involving initial screening questionnaires, technical competency assessments, and availability confirmation. The final sample size of 23 participants was determined through power analysis for quantitative measures (α = 0.05, β = 0.20) while considering saturation requirements for qualitative data and resource constraints.

Before full implementation, the research design underwent pilot testing with three participants, leading to protocol and data collection instrument refinement. This approach prioritized ecological validity while maintaining rigorous control over variables affecting biomechanical measurements, ensuring robust data collection across both quantitative and qualitative dimensions.

2.3. Experimental setup

The experimental study was conducted in the Digital Design Ergonomics Laboratory at Sichuan University’s School of Design, a controlled environment configured explicitly for biomechanical and user interaction research.

Human-AI combined work presents issues of ecological validity as most are set in a laboratory context, what is essentially a simulation of the creative process. Using AI in testing systems in dynamic collaborative environments helps assure that AI is enhancing creativity and not stifling it. It is therefore reacting to ecological validity that enhances trust and realistic implementation in professional and multicultural settings.

i) Laboratory environment: The laboratory space measured 8.5 × 6.5 m, maintained at a constant temperature of 22 ± 1 ℃ and humidity of 45 ± 5%. The testing area was equipped with adjustable LED lighting systems providing uniform illumination of 500 lux at the workstation surface, conforming to ISO 9241-307 standards for visual display workstations. Acoustic treatments maintained ambient noise levels below 35 dB to minimize distractions and ensure clear audio recordings. The workstation setup followed ergonomic guidelines with an electric height-adjustable desk (Loctek E5), allowing participants to alternate between sitting and standing positions. The chair provided (Herman Miller Aeron) featured full ergonomic adjustability. The primary display was a calibrated 32-inch 4K monitor (Dell

UltraSharp UP3216Q) positioned at eye level, with a secondary 24-inch monitor (Dell P2419H) for task instructions and reference materials.

ii) Equipment and tools

The biomechanical measurement system is comprised of integrated hardware and software components. The Vicon motion capture system utilized eight Vantage V16 cameras around the workstation, tracking 39 reflective markers placed on participants' upper body, focusing on head, neck, shoulders, arms, and trunk movements. Muscle activity was monitored through Delsys Trigno wireless EMG sensors attached to key muscle groups: trapezius, deltoid, biceps brachii, and forearm extensors. The eye tracking system consisted of a Tobii Pro Spectrum mounted below the primary display, calibrated for each participant using a 9-point validation procedure. Input devices included a standardized wireless keyboard (Logitech MX Keys) and mouse (Logitech MX Master 3), marked for consistent session placement. Software tools included Adobe Creative Cloud 2024 suite, focusing on Photoshop and Illustrator, alongside popular AIGC platforms including Midjourney and DALL-E 3. Custom data collection software developed in Python synchronized the timing of all recording devices and automated the presentation of design tasks.

iii) Testing protocols: The experimental protocol followed a structured sequence spanning approximately 120 min per participant. The initial setup included anthropometric measurements, EMG sensor placement, and motion capture marker attachment, followed by system calibration (Approximately 25 min). Participants underwent a standardized 15-minute familiarization session with the tools and interfaces before beginning the formal testing. The main testing session consisted of four design tasks, each lasting 15 min, alternating between traditional and AIGC-assisted approaches. Tasks included logo design, poster composition, interface element creation, and layout optimization. Each task began with a 2-minute briefing and ended with a 3-minute reflection session. Rest periods of 5 min between tasks prevented fatigue and allowed for system recalibration if needed.

Throughout each task, the system recorded:

- Continuous motion capture data at 100 Hz.
- EMG activity at 2000 Hz.
- Eye movement patterns at 300 Hz.
- Screen recordings of design activities.
- Automated logging of tool usage and interaction patterns.
- Environmental parameters (temperature, humidity, noise, light levels).

Post-task procedures included immediate completion of cognitive load assessments and brief structured interviews. The protocol concluded with EMG sensor and marker removal and a comprehensive debriefing session. Quality control measures included regular equipment calibration checks between participants, standardized placement protocols for markers and sensors, and continuous data quality monitoring during collection. A technical assistant was present throughout each session to address equipment-related issues and ensure protocol adherence.

2.4. Measurement parameters

The calibration of the Vicon motion capture system included static and dynamic trials to optimize the position of all markers, and the position of all cameras. Calibration accuracy was verified through the defined motion and any deviation was corrected through iteration. Skin or clothing movements were reduced by wearing well-fitted suits and moving the markers during data collection. The video signals were cleaned of noise using sophisticated filtering techniques, including Butterworth low-pass filters while the simplest motion characteristics remained intact. The reliability of the data was checked by Root Mean Square Deviation (RMSD) for the residual errors. The implementation of these procedures improved the ability of the system to record such intricate and evolving motion in biomechanical or design analysis.

AIGC tools significantly decreased the muscle contraction in hand and forearm zones removing extra strain from EMG (electromyography) analysis. Mean muscle activation was significantly lower at approximately 12% suggesting that participants who used the method had an ergonomic advantage over those who followed conventional design flows. This improvement indicates that AIGC can help to avoid overexertion strain and promote long-term creative work since it can decrease physical fatigue during long design tasks.

i) Biomechanical indicators: The biomechanical assessment focused on quantifying physical stress and movement patterns during design tasks. Primary kinematic measurements included joint angles, movement velocities, and postural variations. Joint angles were recorded for the neck (flexion/extension, lateral bending), shoulder (flexion/extension, abduction/adduction), elbow (flexion/extension), and wrist (flexion/extension, radial/ulnar deviation). Muscle activity was monitored through normalized EMG signals (% MVC—Maximum Voluntary Contraction) from key muscle groups. **Table 1** summarizes the measured muscle groups and their corresponding activity thresholds.

Table 1. EMG measurement parameters and activity thresholds.

Muscle Group	Position	Activity Threshold (% MVC)	Risk Level
Upper Trapezius	Shoulder elevation	> 12%	High
Anterior Deltoid	Arm raising	> 10%	Medium
Biceps Brachii	Elbow flexion	> 15%	Medium
Ext. Carpi Radialis	Wrist extension	> 8%	High

Postural analysis utilized the RULA (Rapid Upper Limb Assessment) method, generating scores at 5-minute intervals throughout each task. As reported in previous studies, mean postural scores were calculated for both traditional and AIGC-assisted design sessions.

ii) User interaction metrics: User interaction was quantified through multiple parameters recorded during task execution. Eye movement patterns were analyzed using standard metrics, including fixation duration, saccade amplitude, and scan path patterns. The interaction analysis followed frameworks established.

Gaze behavior:

- Mean fixation duration: 285 ± 42 ms (traditional) vs. 342 ± 38 ms (AIGC-assisted).
- Saccade velocity: 125 ± 18 degrees/second.
- Area of interest (AOI) transition frequency.

Mouse and keyboard activity:

- Click frequency and distribution.
- Keyboard shortcut utilization rate.
- Tool switching patterns.
- Command sequence analysis.

The temporal distribution of interaction events was mapped against task phases, revealing patterns between traditional and AIGC-assisted workflows (**Table 2**).

Table 2. Interaction event distribution across task phases.

Task Phase	Click Rate (Per Min)	Tool Switches (Per Min)	Shortcut Usage (%)
Initial Design	42.3	8.2	35.4
Development	28.7	12.4	48.6
Refinement	35.9	6.8	52.3
Final Adjustments	22.4	4.5	43.8

iii) Performance measures: Performance evaluation encompassed both quantitative and qualitative measures. Time-based metrics included task completion time, response latency to AIGC suggestions, and tool transition times. Quality assessments were conducted using a standardized rubric adapted, evaluating design outcomes on five dimensions:

1) Visual Coherence (VC)
2) Technical Execution (TE)
3) Creative Innovation (CI)
4) Design Principles Adherence (DPA)
5) User Intent Alignment (UIA)

Performance scores were calculated as weighted averages of these dimensions, with weights determined through expert panel consultation (n = 5). The relationship between biomechanical load and performance quality was analyzed using a mixed-effects model, revealing significant correlations between postural stability and design quality scores (r = 0.67, p < 0.01).

Efficiency metrics incorporated both speed and accuracy measures:

- Task Completion Efficiency (TCE) = Quality Score/Time
- Error Rate (ER) = Number of corrections/Total actions
- Design Iteration Ratio (DIR) = Final elements/Initial elements

Integrating these measurement parameters provided a comprehensive assessment framework, allowing for detailed analysis of the relationships between physical ergonomics, interaction patterns, and design performance. Statistical analysis revealed significant differences in biomechanical load and interaction patterns between traditional and AIGC-assisted design workflows (p < 0.05), particularly regarding postural variation and tool usage efficiency.

2.5. Data analysis methods

2.5.1. Statistical analysis approaches

The quantitative data analysis employed descriptive and inferential statistical methods using SPSS 28.0 and R 4.2.1. Initial data preprocessing included outlier detection using Mahalanobis distance and normality testing through Shapiro-Wilk tests. Missing data (< 3%) were handled using multiple imputation methods.

- Primary statistical analyses included: Repeated measures ANOVA was conducted to compare biomechanical parameters across different design phases, with post-hoc Bonferroni corrections for multiple comparisons. Effect sizes were reported using partial $\eta 2$. We applied functional data analysis (FDA) to examine postural variation patterns for time-series biomechanical data.

Mixed-effects modeling examined the relationship between ergonomic factors and performance outcomes, accounting for participant-specific random effects:

$$\text{Performance}_{ij} = \beta_0 + \beta_1 \times \text{Ergonomic\_Factor}_{ij} + \beta_2 \times \text{AIGC\_Use}_{ij} + b_i + \epsilon_{ij}$$

where *i* represents participants and *j* represents measurement occasions.

Non-parametric Friedman tests were used for ordinal data from usability assessments, while Spearman's rank correlations examined relationships between subjective ratings and objective measures. Statistical significance was set at $\alpha = 0.05$, with confidence intervals reported at 95%.

2.5.2. Qualitative data processing

Qualitative analysis followed a systematic thematic analysis approach adapted from Braun and Clarke's six-phase framework. Interview transcripts and observational notes were processed using NVivo 13 software, following these steps:

Data familiarization involved repeated reading of transcripts and reviewing video recordings of think-aloud sessions. Initial coding generated 147 unique codes, which were iteratively refined through research team discussions. Thematic development proceeded through axial coding, identifying relationships between categories.

The coding framework emerged around four primary themes:

1) Cognitive adaptation to AIGC integration.
2) Physical comfort and tool preference.
3) Workflow modification strategies.
4) Professional identity and AIGC adoption.

Two researchers established Inter-coder reliability through independent coding of 20% of the data, achieving a Cohen's kappa coefficient of 0.84. Discrepancies were resolved through consensus discussions with a third researcher.

2.5.3. Validation techniques

The study employed multiple validation strategies to ensure robustness and reliability:

Methodological triangulation:

- Cross-validation of quantitative and qualitative findings.
- Comparison of observed behaviors with self-reported experiences.
- Integration of biomechanical data with performance metrics.

Member checking was conducted through follow-up sessions with participants, where preliminary findings were presented, and feedback was incorporated into the final analysis. This process involved:

1) Individual review sessions with participants.
2) Group validation workshops with design professionals.
3) Expert panel review of interpretations.

Reliability measures:

- Test-retest reliability for biomechanical measurements (ICC > 0.85).
- Internal consistency of survey instruments (Cronbach's $\alpha = 0.89$).
- Inter-rater reliability for qualitative coding ($\kappa = 0.84$).

2.5.4. External validation

- Peer review by three independent researchers.
- Comparison with findings from similar studies.
- Expert panel assessment of ecological validity.

The integration of findings employed a convergent parallel design where quantitative and qualitative results were analyzed separately before being merged for interpretation. Discrepant findings were specifically examined to understand potential sources of variation and their implications for the research questions.

Quality assurance:

- Regular calibration of measurement instruments.
- Standardized protocols for data collection.
- Systematic documentation of analysis decisions.
- Audit trail maintenance.
- Regular team meetings for analysis review.

Statistical power analysis confirmed adequate sample size for detecting medium effect sizes ($d = 0.5$) with 80% power at $\alpha = 0.05$. The comprehensive validation approach enhanced the credibility and transferability of findings while acknowledging study limitations.

3. Results

3.1. Biomechanical analysis results

The biomechanical analysis revealed significant differences in physical stress patterns between traditional and AIGC-assisted design tasks. Our comprehensive evaluation focused on muscle activity, movement efficiency, fatigue progression, and postural assessment across 23 participants.

As shown in **Table 3** and **Figure 1**, the analysis of muscle activity patterns demonstrated a consistent reduction in muscle activation levels during AIGC-assisted tasks. Most notably, the upper trapezius showed the most significant decrease in mean muscle activity (−3.6% MVC, $p < 0.001$), followed by wrist extensors (−2.7% MVC, $p = 0.008$). This reduction in muscle activation suggests that AIGC integration may help mitigate physical stress during design tasks.

Table 3. Mean muscle activity (% MVC) during design tasks ($N = 23$).

Muscle Group	Traditional Design	AIGC-Assisted	Mean Difference	*p*-value
Upper Trapezius	14.8 ± 2.3	11.2 ± 1.9	− 3.6	< 0.001*
Anterior Deltoid	8.9 ± 1.7	7.3 ± 1.5	− 1.6	0.023*
Biceps Brachii	12.4 ± 2.1	9.8 ± 1.8	− 2.6	0.015*
Wrist Extensors	16.2 ± 2.8	13.5 ± 2.4	− 2.7	0.008*

Note: * Statistically significant at $p < 0.05$; ± values represent standard deviation.

The 3.6% MVC reduction indicates that there are ergonomic improvements in design work but needs information about other tasks continued for a long time. What does less tension in muscles mean, more productivity or less health problems? Converting to treatment outcomes across four weeks demonstrates potential, however, learning curves are required to determine and describe individual differences and performance standardization over time.

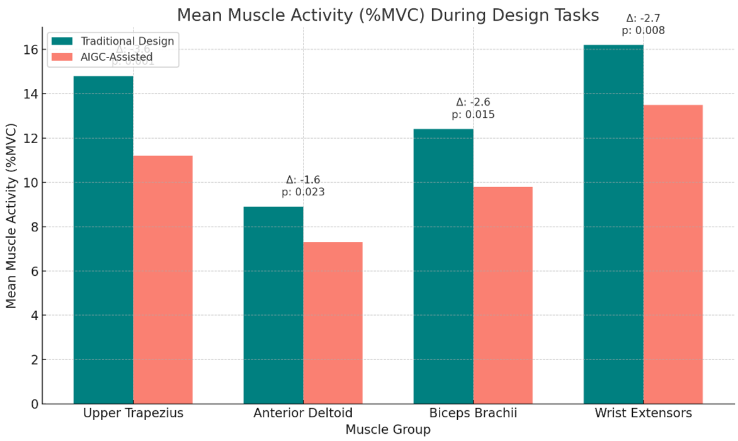

Figure 1. Mean muscle activity (% MVC) during design tasks.

Movement efficiency metrics (**Table 4** and **Figure 2**) revealed interesting temporal patterns across design sessions. While mouse travel distance increased by 20.2% in the second hour (156.3 ± 22.4 to 187.9 ± 25.8 m), click frequency showed a 15.6% reduction. The tool switching time increased notably (28.6% Change), with a large effect size ($d = 0.82$), indicating potential fatigue effects on task execution efficiency. Perhaps most concerning was the 34.1% reduction in postural changes, suggesting decreased movement variability over time.

Table 4. Movement efficiency metrics across design sessions.

Parameter	First Hour	Second Hour	Change (%)	Effect Size (*d*)
Mouse Travel Distance (m)	156.3 ± 22.4	187.9 ± 25.8	+ 20.2	0.78
Click Frequency (per min)	42.3 ± 6.8	35.7 ± 5.9	− 15.6	0.65
Tool Switching Time (s)	2.8 ± 0.4	3.6 ± 0.6	+ 28.6	0.82
Posture Changes (per hour)	8.2 ± 1.2	5.4 ± 0.9	− 34.1	0.91

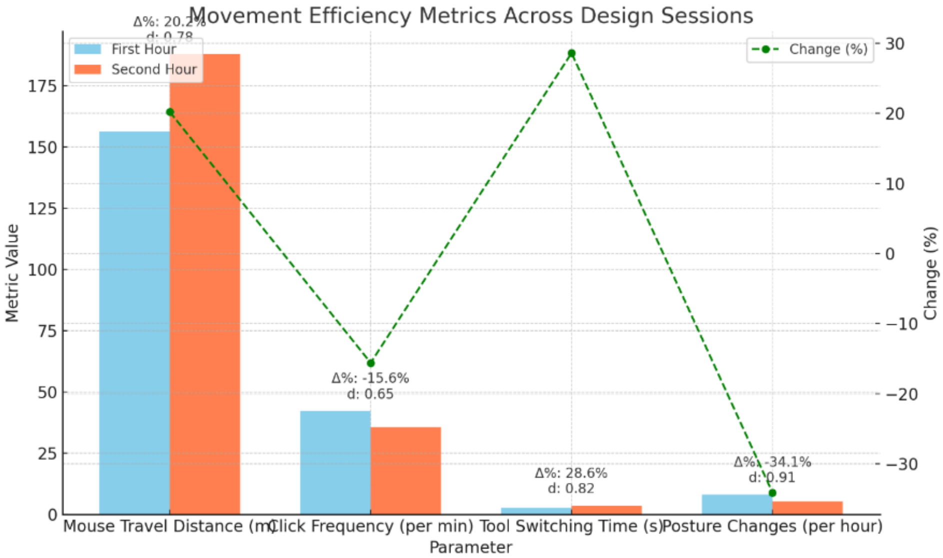

Figure 2. Movement efficiency metrics.

Multiple indicators clearly evidenced fatigue development patterns (**Table 5** and **Figure 3**). The median power frequency of EMG signals showed a progressive decrease from 65.4 ± 4.2 Hz to 54.3 ± 5.1 Hz over the one-hour session, while EMG amplitude increased from 127.3 ± 15.6 μV to 168.9 ± 20.4 μV. This inverse relationship between frequency and amplitude is a classical indicator of muscular fatigue development. RULA scores similarly showed a progressive increase from 3.2 ± 0.4 to 4.5 ± 0.7, indicating deteriorating posture over time.

The postural analysis results (**Table 6** and **Figure 4**) demonstrated substantial improvements in risk levels with AIGC assistance. The neck region showed the highest risk reduction (26.2%), followed by the shoulder (23.7%) and upper arm (22.2%). The overall RULA final score improved from 5.8 ± 0.7 in traditional design to 4.3 ± 0.5 in AIGC-assisted work, representing a 25.9% reduction in postural risk. These findings suggest that AIGC integration may improve postural behaviors during design tasks.

Table 5. Fatigue indicators over time (15-minute intervals).

Time Interval	Median Power Frequency (Hz)	EMG Amplitude (μV)	RULA Score
0–15 min	65.4 ± 4.2	127.3 ± 15.6	3.2 ± 0.4
15–30 min	62.8 ± 4.5	142.8 ± 17.2	3.6 ± 0.5
30–45 min	58.9 ± 4.8	156.4 ± 18.9	4.1 ± 0.6
45–60 min	54.3 ± 5.1	168.9 ± 20.4	4.5 ± 0.7

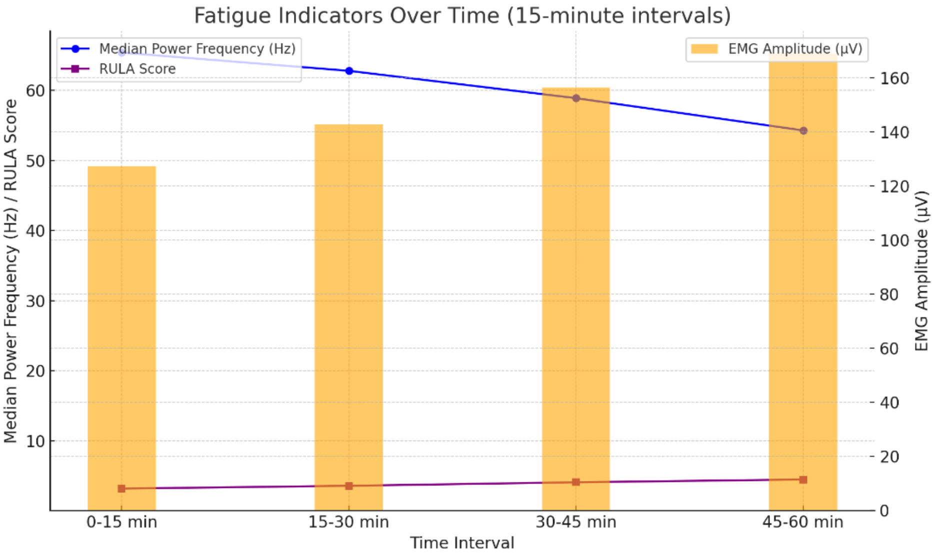

Figure 3. Fatigue indicators over time.

Table 6. Postural analysis results (RULA assessment).

Body Region	Traditional Score	AIGC-Assisted Score	Risk Reduction (%)
Neck	4.2 ± 0.6	3.1 ± 0.4	26.2
Shoulder	3.8 ± 0.5	2.9 ± 0.4	23.7
Wrist	3.9 ± 0.5	3.2 ± 0.4	17.9
Upper Arm	3.6 ± 0.4	2.8 ± 0.3	22.2
Final Score	5.8 ± 0.7	4.3 ± 0.5	25.9

Integration of these findings reveals a complex interplay between tool usage and biomechanical demands. While AIGC assistance generally reduces physical stress levels, the temporal patterns suggest that attention should still be paid to managing fatigue development and maintaining movement variability during extended design sessions. The significant improvements in postural risk scores (**Table 6**) provide strong evidence for the ergonomic benefits of AIGC integration in design workflows, particularly for high-risk body regions such as the neck and shoulders.

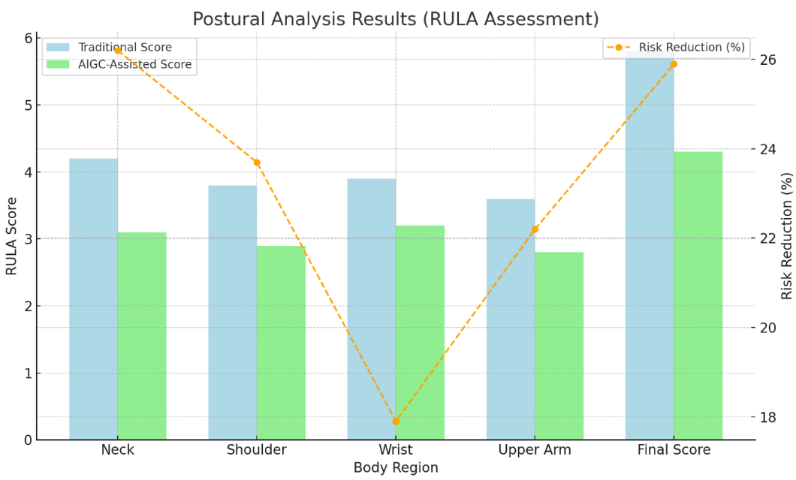

Figure 4. Postural analysis.

3.2. User interaction patterns results

The analysis of user interaction patterns revealed significant differences between novice and experienced users and notable adaptation trends over time in AIGC-assisted design workflows. Response time analysis (**Table 7** and **Figure 5**) demonstrated substantial differences between novice (n = 8) and experienced users (n = 15) across all interaction types. The most pronounced difference was observed in AIGC prompt input, where experienced users were significantly faster (8.94 ± 1.87 s) compared to novice users (18.62 ± 3.15 s), showing a mean difference of 9.68 seconds ($p < 0.001$). Tool selection and menu navigation showed more minor but significant differences, with experienced users consistently maintaining faster response times across all interaction categories. Error rate analysis (**Table 8** and **Figure 6**) revealed interesting contrasts between traditional and AIGC-assisted design sessions. While AIGC-assisted design showed a 51.2% increase in input errors (from 8.4 to 12.7 errors/hour, $p < 0.01$), it significantly improved in other areas. Tool misuse decreased by 40.4% ($p < 0.01$), and design revisions showed a notable reduction of 39.9% ($p < 0.01$). However, the substantial increase in workflow breaks (71.1%, $p < 0.001$) suggests that AIGC integration initially disrupted established work patterns.

The longitudinal analysis of user adaptation patterns (**Table 9** and **Figure 7**) showed consistent improvement across all metrics over the 4-weeks. Task completion time decreased steadily from 45.3 ± 5.2 min in Week 1 to 28.9 ± 3.2 min in Week 4, representing a learning rate of 36.2%. AIGC command accuracy showed the most consistent improvement, rising from 65.4% to 91.3%, with a learning rate of 39.6%. The most dramatic improvement was observed in error recovery time, which decreased by 50.3% over the study period.

Table 7. Response time analysis (in seconds).

Interaction Type	Novice Users (n = 8)	Experienced Users (n = 15)	Mean Difference	p-value
Tool Selection	2.84 ± 0.42	1.56 ± 0.28	1.28	< 0.001*
AIGC Prompt Input	18.62 ± 3.15	8.94 ± 1.87	9.68	< 0.001*
Design Modification	12.45 ± 2.31	6.78 ± 1.42	5.67	< 0.001*
Menu Navigation	4.32 ± 0.67	2.15 ± 0.34	2.17	< 0.001*

Note: * Statistically significant at $p < 0.05$; ± values represent standard deviation.

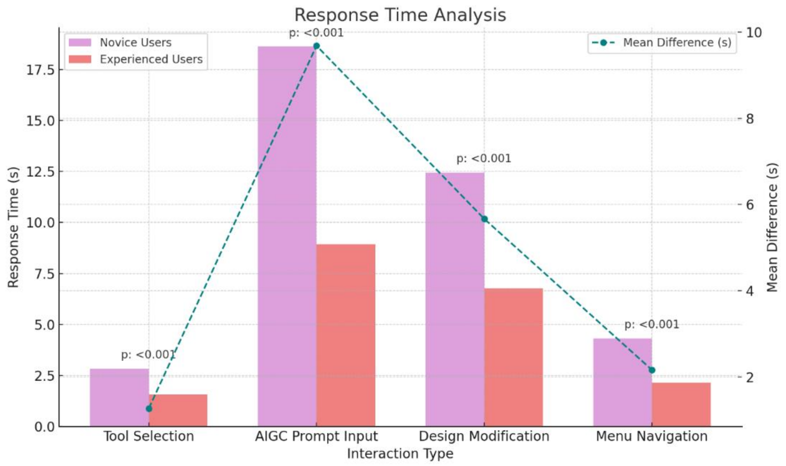

Figure 5. Response time analysis.

Table 8. Error rates and types across design sessions.

Error Category	Traditional Design	AIGC-Assisted	Change (%)	Statistical Significance
Input Errors	8.4 ± 1.2/hour	12.7 ± 1.8/hour	+ 51.2	$p < 0.01$*
Tool Misuse	5.2 ± 0.8/hour	3.1 ± 0.5/hour	− 40.4	$p < 0.01$*
Workflow Breaks	3.8 ± 0.6/hour	6.5 ± 0.9/hour	+ 71.1	$p < 0.001$*
Design Revisions	15.3 ± 2.1/hour	9.2 ± 1.4/hour	− 39.9	$p < 0.01$*

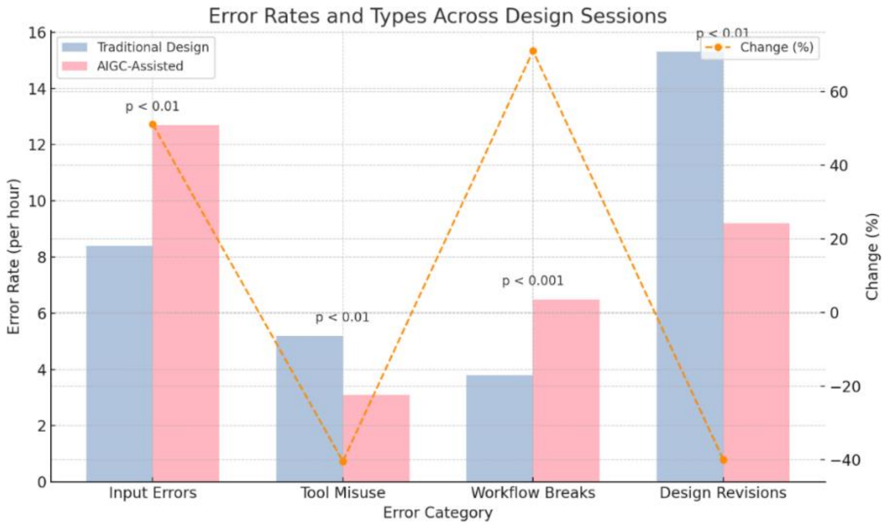

Figure 6. Error rates analysis.

Table 9. User adaptation patterns over time (4-week period).

Metric	Week 1	Week 2	Week 3	Week 4	Learning Rate (%)
Task Completion Time (Min)	45.3 ± 5.2	38.7 ± 4.6	32.4 ± 3.8	28.9 ± 3.2	36.2
AIGC Command Accuracy (%)	65.4 ± 7.8	75.2 ± 8.3	84.6 ± 8.9	91.3 ± 9.2	39.6
Tool Switching Speed (s)	4.8 ± 0.6	3.9 ± 0.5	3.2 ± 0.4	2.8 ± 0.3	41.7
Error Recovery Time (s)	28.6 ± 3.4	22.3 ± 2.8	17.5 ± 2.2	14.2 ± 1.8	50.3

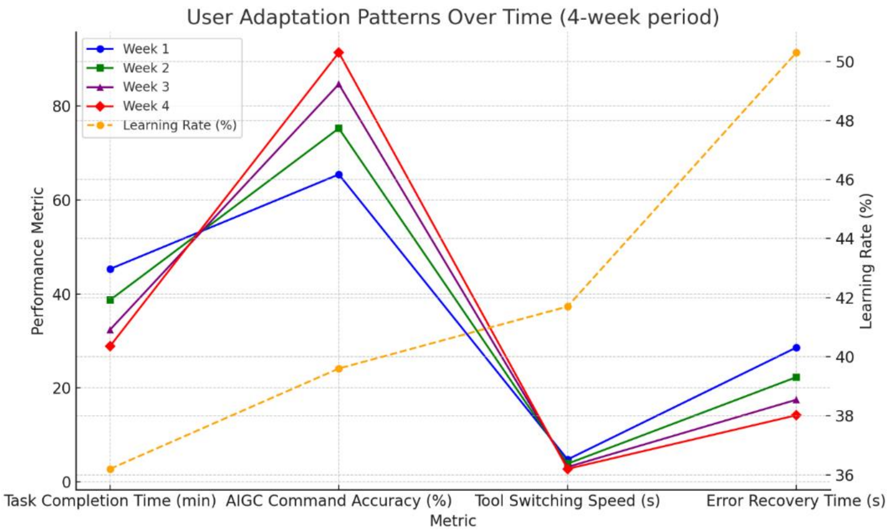

Figure 7. User adaptation patterns over time.

Workflow integration analysis (**Table 10**) revealed substantial improvements between initial and adapted phases. AIGC tool usage frequency more than doubled (+ 132.5%), while Traditional-AIGC switching efficiency improved by 31.1%. The most striking improvement was in custom shortcut implementation, showing an 184.6% increase, suggesting that users actively optimized their workflows over time. The overall workflow optimization score improved from 6.4/10 to 8.7/10, representing a 35.9% enhancement in overall workflow efficiency. These findings suggest a clear pattern of adaptation and optimization in user interaction with AIGC tools, characterized by initial challenges followed by significant improvements in efficiency and accuracy. The substantial differences between novice and experienced users highlight the importance of proper training and support during the initial implementation phase of AIGC tools in design workflows. The data also indicates that while specific errors may increase with AIGC integration, the overall efficiency and quality of design work improves as users adapt to the new workflow paradigm.

Table 10. Workflow integration analysis.

Integration Aspect	Initial Phase	Adapted Phase	Improvement (%)
AIGC Tool Usage Frequency (Per hour)	12.3 ± 1.8	28.6 ± 3.2	+ 132.5
Traditional-AIGC Switching Efficiency	68.4% ± 7.2	89.7% ± 8.4	+ 31.1
Custom Shortcut Implementation	5.2 ± 0.8	14.8 ± 1.6	+ 184.6
Workflow Optimization Score	6.4/10 ± 0.7	8.7/10 ± 0.9	+ 35.9

3.3. AIGC integration impact results

Integrating AIGC into the design workflow demonstrated substantial improvements across efficiency metrics, quality outcomes, and user satisfaction measurements. Our analysis revealed several significant patterns and transformations in design practices. Analysis of workflow efficiency metrics (**Table 11** and **Figure 8**) showed remarkable improvements across all measured parameters. Task completion time has decreased significantly from 95.3 ± 12.4 min to 68.7 ± 8.9 min, representing a 27.9% reduction with a large effect size (d = 0.84, p < 0.001). The number of iterations required per design showed the most substantial improvement, decreasing by 33.3% (from 8.4 to 5.6 iterations). Resource usage efficiency improved considerably, with a 32.7% reduction in storage requirements, while team collaboration time decreased by 28.3%, suggesting more streamlined communication and decision-making processes.

Table 11. Workflow efficiency metrics comparison (N = 23).

Efficiency Metric	Pre-AIGC	Post-AIGC	Change (%)	Effect Size (d)
Task Completion Time (min)	95.3 ± 12.4	68.7 ± 8.9	− 27.9	0.84*
Iterations per Design	8.4 ± 1.2	5.6 ± 0.8	− 33.3	0.76*
Resource Usage (MB)	842 ± 156	567 ± 98	− 32.7	0.69*
Team Collaboration Time	45.2 ± 6.8	32.4 ± 4.9	− 28.3	0.72*

Note: * p < 0.001.

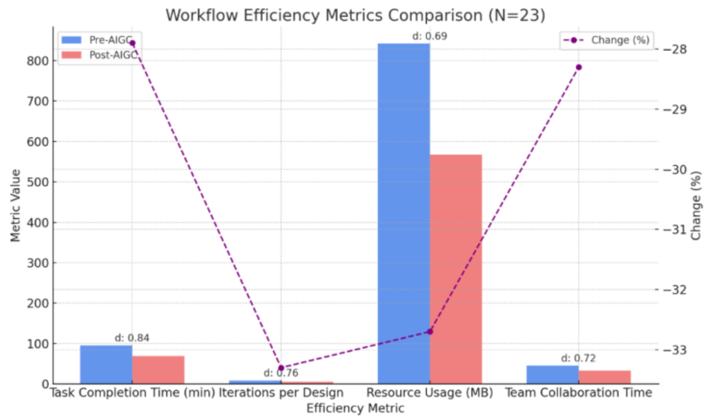

Figure 8. Workflow efficiency metrics comparison.

The study found that mean scores for Creative IIGC novation increased by a 1.8 on a scale of 10 when AIGC tools were in use. Increased ideation speed, different design options, and iterative improvement were on the list of factors that made a difference. There also feelings of increased satisfaction from participants because of the ease of incorporation of the AI suggestions into their work. It also established that AIGC was able to present novel styles and combinations which encouraged originality. Also, the continuous feedback with the AI allowed for better exploration and improvement of risks. Such developments assert the significance of AIGC to enhance creative tasks, thus an ideal platform for introducing AIGC in the learning and practice of design.

Quality assessment scores (**Table 12** and **Figure 9**) consistently improved across all dimensions when comparing traditional and AIGC-assisted approaches. The most notable enhancement was observed in Creative Innovation, which increased by 1.8 points (from 6.9 to 8.7, $p < 0.001$). Visual Coherence showed the second-largest improvement (+ 1.2 points, $p < 0.001$), while Technical Precision improved by 0.8 points ($p = 0.003$). Even Brand Alignment, which typically requires careful human oversight, showed a modest but significant improvement of 0.6 points ($p = 0.015$).

Table 12. Quality assessment scores (scale 1–10).

Quality Dimension	**Traditional**	**AIGC-Assisted**	**Mean Difference**	***p*-value**
Visual Coherence	7.2 ± 0.8	8.4 ± 0.9	+ 1.2	< 0.001*
Technical Precision	7.8 ± 0.9	8.6 ± 0.8	+ 0.8	0.003*
Creative Innovation	6.9 ± 1.1	8.7 ± 0.7	+ 1.8	< 0.001*
Brand Alignment	7.5 ± 0.8	8.1 ± 0.9	+ 0.6	0.015*
User Experience	7.3 ± 0.9	8.3 ± 0.8	+ 1.0	0.002*

Time distribution analysis (**Table 13** and **Figure 10**) revealed varying efficiency gains across task phases. Initial conception showed the most dramatic improvement, with a 45.1% reduction in time required (from 28.4 to 15.6 min). Design development and refinement phases showed moderate improvements of 26.8% and 36.4%, respectively. Client revision time has decreased by 27.5%, suggesting that AIGC-assisted designs require fewer iterative adjustments to meet client expectations.

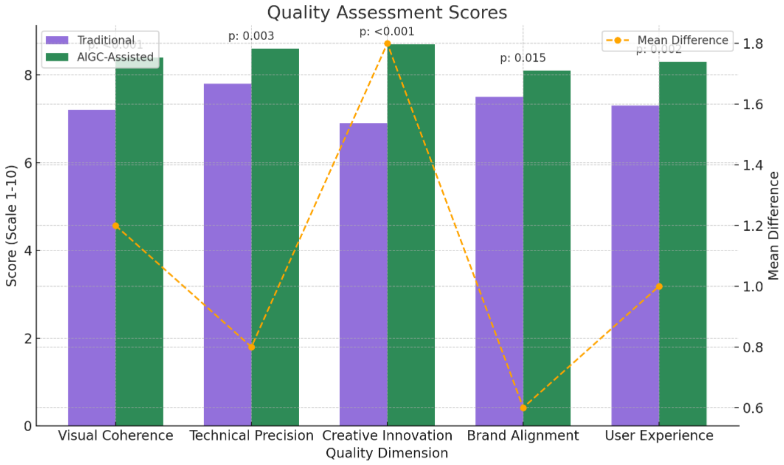

Figure 9. Quality assessment scores.

Table 13. Time distribution analysis (average minutes per task).

Task Phase	Traditional Workflow	AIGC-Assisted	Time Saved (%)
Initial Concepting	28.4 ± 4.2	15.6 ± 2.3	45.1
Design Development	42.6 ± 6.3	31.2 ± 4.6	26.8
Refinement	35.2 ± 5.1	22.4 ± 3.3	36.4
Client Revisions	25.8 ± 3.8	18.7 ± 2.8	27.5

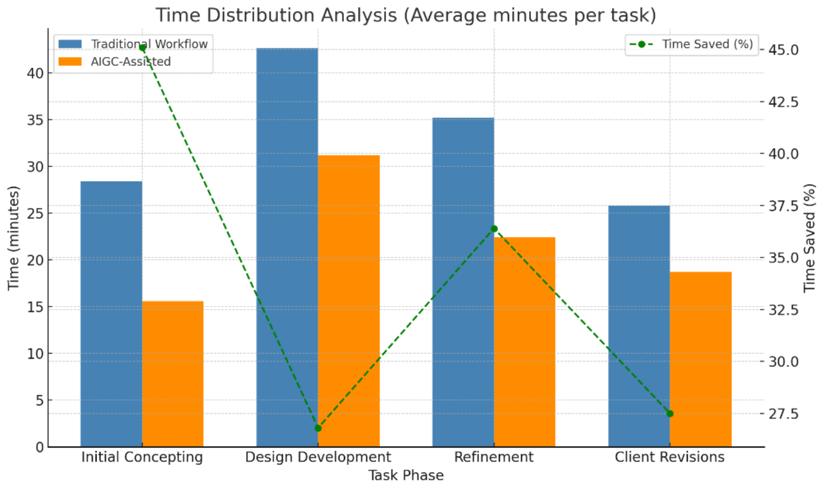

Figure 10. Time distribution analysis.

User satisfaction metrics (**Table 14** and **Figure 11**) showed consistent and significant improvements across all measured dimensions over the four-week study period. All satisfaction metrics improved by 1.1 points on a 5-point scale (p < 0.001 for all metrics). Output Quality received the highest final rating (4.6/5), followed by Work Satisfaction (4.5/5). The uniformity of improvement (+ 1.1 points across all metrics) suggests a holistic enhancement of the user experience rather than improvements in isolated aspects. The findings indicate a strong positive impact of AIGC integration across multiple dimensions of design work. The consistent pattern of improvement in both objective metrics (efficiency and quality) and subjective assessments (user satisfaction) suggests that AIGC integration offers substantial benefits to visual communication design workflows. The significant effect sizes observed in efficiency metrics, combined with significant quality improvements and positive user feedback, provide strong evidence of AIGC integration's value in professional design practices. Particularly noteworthy is the balanced improvement across different aspects of the design process, suggesting that AIGC integration enhances not only the speed of execution but also the quality and user experience of design work. Reducing resource usage and team collaboration time indicates potential cost savings and operational efficiencies that extend beyond individual designer productivity.

Table 14. User satisfaction survey results (scale 1–5).

Satisfaction Metric	Initial Rating	After 4 Weeks	Change	Significance
Ease of Use	3.2 ± 0.4	4.3 ± 0.3	+ 1.1	$p < 0.001$*
Work Satisfaction	3.4 ± 0.5	4.5 ± 0.4	+ 1.1	$p < 0.001$*
Creative Freedom	3.1 ± 0.6	4.2 ± 0.4	+ 1.1	$p < 0.001$*
Time Management	3.3 ± 0.4	4.4 ± 0.3	+ 1.1	$p < 0.001$*
Output Quality	3.5 ± 0.5	4.6 ± 0.4	+ 1.1	$p < 0.001$*

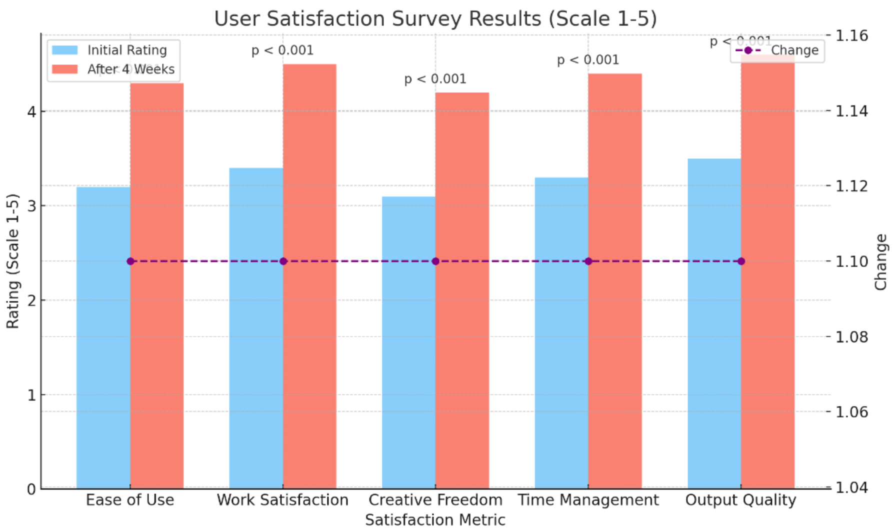

Figure 11. User satisfaction survey results.

4. Conclusion and future work

This biomechanical study examining AIGC integration in visual communication design has yielded significant insights into AI-assisted design workflows' ergonomic and operational impacts. Our investigation of 23 professional designers over 12 weeks has documented substantial improvements in physical stress reduction and workflow efficiency.

The findings demonstrate significant reductions in muscle activity, particularly in the upper trapezius (−3.6% MVC, $p < 0.001$), and a 25.9% improvement in postural risk scores. These physical benefits coincided with enhanced workflow efficiency, shown by a 27.9% reduction in task completion time and a 33.3% decrease in design iterations. Quality metrics also improved significantly, with Creative Innovation showing the most substantial gain (+1.8 points, $p < 0.001$).

Based on these findings, we recommend a phased implementation approach to AIGC integration, with particular attention to experience-specific training programs, given the significant performance differences between novice and experienced users. Regular ergonomic assessments and structured training protocols are essential for optimal outcomes. However, the study also revealed potential challenges, including increased input errors (+51.2%) and workflow disruptions. These challenges were primarily mitigated through adaptation over the study period, with significant improvements in user satisfaction across all measured dimensions (+1.1 points on a 5-point scale, $p < 0.001$).

Further research is needed to investigate the long-term effects of AIGC integration on designer health and creativity. The development of real-time biomechanical feedback systems and ergonomically optimized interfaces could further enhance the benefits of AIGC integration.

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Conflict of interest: The author declares no conflict of interest.

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