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Article

Postural mechanics and artistic control in painting: Investigating the role of movement in artistic creation

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Abstract: Postural mechanics and movement control play fundamental roles in artistic creation, particularly in painting, where precision and fluidity of motion directly influence artistic outcomes. This study investigated the biomechanical relationships between posture, movement, and artistic control in painting practice through a comprehensive analysis of 38 artists (22 Female, 16 Male) ranging from novice to expert-level practitioners in traditional Chinese and contemporary painting techniques. Using an integrated measurement approach combining Motion Capture System (MCS) (Vicon Motion System), electromyography (EMG), and force plate analysis, we examined postural dynamics, movement patterns, and their effects on artistic precision across varied painting conditions. Results revealed significant correlations between postural stability and painting precision ($r = 0.82$, $p < 0.001$), with experienced artists demonstrating superior postural control strategies compared to novices. Analysis of seated versus standing positions showed distinct advantages in stability metrics (88.5 ± 4.2 vs. 82.3 ± 5.6 stability index, $p < 0.01$), though standing positions offered a more excellent range of motion (58.7 cm ± 7.2 cm vs. 42.3 cm ± 5.6 cm brush reach, $p < 0.001$). Environmental factors, particularly easel configuration and lighting conditions, significantly impacted performance, with optimal easel height (90%–105% of eye level) correlating with enhanced precision scores (improvement of 18.4 ± 4.2%, $p < 0.001$). Tool selection analysis demonstrated that medium-length brushes (20 cm–30 cm) provided optimal comfort (8.7 ± 0.9 out of 10) and precision (88.6 ± 3.8 out of 100) scores. Extended painting sessions revealed progressive changes in muscle activation patterns, with expert artists maintaining more consistent movement patterns despite fatigue (8.4 ± 1.2% vs. 18.7 ± 3.2% movement variability, $p < 0.001$). These findings provide quantitative evidence for the importance of proper postural mechanics in artistic creation and offer practical insights for optimizing painting performance through improved biomechanical awareness and environmental setup.

Keywords: postural control; artistic biomechanics; painting technique; motor learning; ergonomics; traditional Chinese painting; movement analysis

1. Introduction

The intersection of artistic expression and biomechanical function presents a fascinating domain for scientific investigation, particularly in painting [1–3]. This study explores the intricate relationship between postural mechanics and artistic control, examining how physical movement patterns influence creative expression and technical execution in painting practice. The research spans traditional Chinese painting techniques and contemporary approaches, comprehensively analyzing artistic creation's biomechanical foundations. The significance of this investigation extends beyond mere ergonomic considerations, delving into the fundamental connection between body mechanics and artistic output. Historical evidence suggests that master painters across cultures have intrinsically understood the importance of movement control and postural stability in their practice, yet systematic scientific analysis of these relationships remains limited [4–6]. In traditional Chinese painting, where brush control and movement fluidity are paramount, the role of postural mechanics becomes particularly crucial, affecting both the physical execution and the aesthetic outcome of the artistic process [7,8].

Contemporary artistic practice has witnessed significant evolution in techniques, tools, and approaches, necessitating a deeper understanding of the biomechanical demands placed on artists [9–11]. The increasing recognition of repetitive strain injuries among professional artists, coupled with the growing interest in evidence-based teaching methodologies, underscores the timeliness of this research [12,13]. Furthermore, integrating traditional wisdom with modern biomechanical analysis offers unique insights into optimal painting practices and injury prevention strategies [14–16]. This study aimed to address several critical research questions: How do different postural configurations affect painting precision and control? What role do muscle memory and motor learning play in artistic technique development? How do environmental factors and tool selection influence artist performance and fatigue? Through examining these questions, we sought to bridge the gap between artistic practice and biomechanical science, providing evidence-based insights for both practitioners and educators [17–19].

The research methodology combined quantitative biomechanical analysis with qualitative assessment of artistic outcomes, employing state-of-the-art motion capture technology, electromyography (EMG), and force plate measurements. This comprehensive approach allowed for a detailed examination of movement patterns, muscle activation, and postural control across various painting techniques and experience levels. The study included 38 participants from diverse artistic backgrounds, representing both traditional Chinese painting practitioners and contemporary artists, providing a rich dataset for comparative analysis. The findings presented in this paper offer novel insights into the relationship between physical movement and artistic creation, with practical implications for art education, studio setup, and painting technique development. By examining the biomechanical foundations of painting practice, this research contributes to understanding how physical mechanics influence artistic expression and technical mastery in the visual arts. The results suggest specific strategies for optimizing postural control and movement efficiency, potentially enhancing artistic performance and practitioner well-being [20–25].

The interaction between postural mechanics and motor control is presented when artists can sway and paint simultaneously. In painting, stances are fundamental in controlling canvas dimension, characteristics of tools, and style. The actions of painting have well-defined wrist and finger actions in Chinese brush paintings and more massive actions involving the shoulder and elbow in contemporary oil paintings. This means that a scientific analysis of movement mechanics must be conducted to understand those differences. By using motion capture systems in synergy with the analysis of biomechanics, specific movements of the human body can be recorded, and the effects of various painting approaches on people’s posture and movement process, as well as painting results, can be identified [26–30]. To that end, this study intertwines art and science by examining the mechanics behind creativity. It aims to create ergonomic knowledge for artists and encourage a multidisciplinary approach to interpreting art [31–35].

Our investigation builds upon previous motor control, ergonomics, and art practice research while introducing new perspectives on integrating traditional artistic wisdom with contemporary biomechanical analysis. The findings presented here have significant implications for art education, studio practice, and developing evidence-based teaching methodologies in the visual arts. Through this research, we aim to contribute to the growing body of knowledge at the intersection of art and science, offering practical insights for artists, educators, and researchers in both fields [36–40].

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

2. Methodology

2.1. Population

Age affects artistic performance through biomechanics, such as loss of joint flexibility, reduced grip strength, and slower motor reaction time. In some comparisons, younger artists may show better dynamic control and stamina, while in others, the older artists may use the experience to make up for frailty and inflexibility, using precise movements in place of energy to create perfect performances [41–45].

The study recruited 38 Chinese artists (n = 38) representing various regions across China, encompassing traditional and contemporary practitioners. The participant pool demonstrated a balanced gender distribution, with 22 female (57.9%) and 16 male (42.1%) artists ranging in age from 25 to 65 years (M = 42.3, SD = 11.7). This diverse age range allowed for a comprehensive examination of postural mechanics across different career stages and experience levels, with professional experience from 5 to 35 years (M = 15.8 years, SD = 8.4). Geographically, participants were strategically selected from major artistic centers across China to ensure representation of various regional artistic traditions and contemporary practices. The largest contingent came from Beijing (n = 12), followed by Shanghai (n = 8), with additional participants from Guangzhou (n = 6), Xi'an (n = 7), and Hangzhou (n = 5). This geographic distribution provided insights into potential variations in artistic techniques and postural habits across China's regions and artistic communities [46–50].

The participants' educational backgrounds reflected the diverse pathways in Chinese art education, with the majority holding formal academic qualifications. Twenty-five participants had completed Bachelor's degrees in Fine Arts, while ten held Master's degrees in related artistic disciplines. Three participants had undergone traditional apprenticeship training, bringing valuable insights from classical Chinese artistic training methods. In terms of artistic specialization, the study included fifteen practitioners of traditional Chinese painting, twelve contemporary oil painting artists, and seven mixed media artists, ensuring a comprehensive representation of different painting techniques and their associated postural requirements [51–56].

From **Table 1** is the motion capture calibration of the cameras and sensors requires system tuning for spatial and temporal accuracy. This is followed by calibrating a capture volume by moving a calibration wand or an object with a known dimension in the workspace for mapping Camera alignment. Cameras are triggered simultaneously to capture frames at an agreed interval, and reflective markers are placed on the segment of interest at specific body locations. The validation process, therefore, requires test recordings to ensure that markers are visible, that the system has a high level of accuracy, and that measurement errors have not been made due to occlusions or misalignment. Periodic calibration is crucial since it prevents fluctuations in output when performing long experiments such as painting fine motor precision.

Table 1. Demographic characteristics of Chinese artists (N = 38).

Characteristic	Category	*n*	Percentage (%)	Mean ± SD
Gender	Female	22	57.9	
	Male	16	42.1	
				42.3 ± 11.7
Age (years)	25–35	12	31.6	
	36–45	14	36.8	
	46–55	8	21.1	
	56–65	4	10.5	
				15.8 ± 8.4
Professional experience	5–10 years	10	26.3	
	11–20 years	16	42.1	
	21–35 years	12	31.6	
Geographic location	Beijing	12	31.6	
	Shanghai	8	21.1	
	Guangzhou	6	15.8	
	Xi’an	7	18.4	
	Hangzhou	5	13.2	
Educational background	Bachelor’s in Fine Arts	25	65.8	
	Master’s in Fine Arts	10	26.3	
	Traditional Apprenticeship	3	7.9	
Artistic specialization	Traditional Chinese	15	39.5	
	Contemporary Oil	12	31.6	
	Mixed Media	7	18.4	

2.2. Data collection setup

2.2.1. Motion capture system (MCS)

The study employed a comprehensive MCS to record and analyze artists’ postural mechanics during painting sessions. A 12-camera Vicon Motion Capture

System (Vicon Nexus 2.12, Oxford Metrics, UK) was deployed, operating at a sampling rate of 100 Hz. The cameras were strategically positioned in a 360-degree configuration around the painting workspace, creating a capture volume of 4m × 4m × 3m to ensure complete coverage of all painting positions and movements. To enhance tracking accuracy, 39 retroreflective markers (14mm diameter) were placed on anatomical landmarks following the Plug-in Gait marker set protocol, with additional custom markers placed on the brush-holding hand for detailed analysis of brush manipulation. Supplementary to the optical system, wireless inertial measurement units (IMUs) (Xsens MTw Awinda, Netherlands) were attached to key body segments, sampling at 60 Hz. These sensors provided continuous data streams of acceleration, angular velocity, and orientation, particularly valuable when optical markers occluded during complex painting maneuvers. The dual-system approach ensured robust data collection and enabled cross-validation of measurements.

2.2.2. Recording protocols

The recording protocol was standardized across all participants while accommodating individual artistic styles and preferences. Each session began with a static calibration pose and a series of range-of-motion trials to establish participant-specific movement boundaries. The main recording session was structured as shown in **Table 2**.

Table 2. Data collection setup and protocol parameters.

Category	Parameters	Specifications
Environmental setup	Canvas position	Adjustable easel at participant's eye level
	Lighting	1000 lux at canvas surface
	Temperature	22°C (±1°C)
	Workspace	Unrestricted movement area
Recording schedule	Session duration	3 × 30-minute painting sessions
	Rest periods	10 min between sessions
	Total duration	90 min per participant
Task structure	Session 1	Preliminary sketching and composition
	Session 2	Primary painting phase
	Session 3	Detail work and finishing
Data collection parameters	Motion capture	Continuous recording throughout sessions
	Video recording	Time-synced, three angles (front, side, overhead)
	Event marking	Manual triggers for technique transitions
	Calibration	Regular system checks between sessions
Quality assurance	Real-time monitoring	Marker visibility and tracking quality
	Data management	Immediate backup after each session
	Environmental recording	Conditions and technical notes
	Documentation	Technical issues and marker adjustments

The protocol was designed to minimize interference with the natural painting while maintaining data quality and consistency. Participants were encouraged to work in their usual manner, with the only constraint being to remain within the calibrated capture volume. Technical staff monitored recordings discreetly from an adjacent room to avoid influencing artist behavior while maintaining the ability to address any technical issues promptly. Before data collection, each participant was familiarized with the setup during a 15-minute practice session, allowing them to acclimate to the presence of markers and ensure comfort with the recording environment. This preparation phase was crucial for obtaining natural movement patterns during the recording sessions. A standardized set of verbal instructions was provided to all participants, emphasizing the importance of maintaining their typical painting approach while remaining mindful of staying within the capture volume. The instructions were delivered in Mandarin Chinese to ensure clear understanding and consistent implementation across all participants.

2.3. Variables and measurement

This study examined a range of biomechanical and performance variables to evaluate the relationship between postural mechanics and artistic control in painting. The variables selected were categorized into three main areas: kinematic, kinetic, and performance measures, each providing insights into different aspects of postural dynamics and painting precision.

2.3.1. Kinematic variables

Kinematic variables focused on capturing the range and quality of movement involved in painting tasks. These measurements were derived from the motion capture data and included:

- Joint Angles: Real-time angular data of the shoulder, elbow, wrist, and spine joints, focusing on the dominant arm. These angles were measured in degrees and tracked continuously to assess how different painting styles impacted joint movement patterns.
- Velocity and Acceleration: Linear and angular velocities and accelerations of the brush hand and upper body were recorded to analyze the speed and smoothness of movements across different tasks. Peak and average velocities, as well as changes in velocity, were calculated to observe control over brushstrokes.
- Hand Path Trajectory: The 3D spatial trajectory of the brush hand was recorded to capture the path taken by the artist's hand during strokes. Specific metrics such as total path length and curvature were extracted to analyze the fluidity and consistency of strokes.

2.3.2. Kinetic variables

Kinetic variables provided insights into the forces exerted by the participants and the physical demands of different painting postures:

- Grip Force: For those using brushes fitted with sensors, grip force was measured to determine the pressure exerted during different stages of brushstroke application. This force was recorded continuously to capture variations between fine detail work and broader strokes.
- Ground Reaction Force (GRF): In standing postures, force plates were used to measure the ground reaction forces at each foot. These data allowed analysis of

balance, weight distribution, and stability, highlighting the physical load associated with standing and leaning during painting.

- Load on Lower Back and Shoulders: Using data from IMUs, the load on the lower back and shoulders was estimated based on body angles and force data. This measurement indicated strain during prolonged painting sessions, particularly for those engaging in large, expressive movements.

2.3.3. Performance variables

Performance variables assessed the precision and characteristics of brushwork, providing a connection between biomechanics and artistic output:

- Brushstroke Consistency: Variability in stroke length, width, and orientation was measured to assess control. Using video analysis, brushstroke characteristics were segmented and quantified, allowing the comparison of consistency across repetitive strokes.
- Stroke Accuracy: The deviation from an ideal stroke path was measured for tasks requiring precise details. This was particularly relevant in tasks that required detailed lines, where slight deviations would indicate postural impacts on precision.
- Task Completion Time: The time taken to complete predefined painting tasks was recorded, indicating efficiency and control across different posture conditions.

2.3.4. Measurement tools and techniques

- Motion Capture System: The 12-camera Vicon system captured kinematic variables at a 100 Hz sampling rate, ensuring high-resolution data for joint angles, velocities, and hand trajectories.
- Inertial Measurement Units (IMU): Wireless IMU attached to key body segments continuously recorded acceleration, angular velocity, and orientation at 60 Hz. These units were critical for obtaining kinetic data, especially for measuring lower back and shoulder loads and movement.
- Force Plates: GRF data was collected using force plates positioned beneath each foot. This setup allowed analysis of balance shifts and weight distribution, particularly during standing postures.
- Grip Force Sensors: Force-sensitive resistors recorded grip force data in real-time for participants using sensor-equipped brushes. This data was synchronized with motion capture to align grip variations with specific brushstroke dynamics.
- Video Recording: High-definition video recordings from multiple angles (front, side, and overhead) were time-synced with motion capture data to provide visual context for each stroke. This method enabled detailed post-analysis of brushstroke characteristics and task performance.

From **Table 3** is the integrating these variables and precise measurement techniques, the study captured a comprehensive dataset on the physical demands, movement quality, and control dynamics involved in painting. This approach allowed for an in-depth analysis of how posture and movement directly influence artistic precision, control, and efficiency. The following table lists the measurements and variables.

Table 3. Variables and measurement overview.

Category	Variable	Measurement method	Units
Kinematic variables	Joint angles	Motion capture system (Vicon, 100 Hz)	Degrees (°)
	Velocity	Motion capture system (Vicon, 100 Hz)	Meters per second (m/s)
	Acceleration	Motion capture system (Vicon, 100 Hz)	Meters per second squared (m/s^2)
	Hand path trajectory	Motion capture system (Vicon, 100 Hz)	Meters (m)
Kinetic variables	Grip force	Force-sensitive resistors on the brush handle	Newtons (N)
	Ground reaction force (GRF)	Force plates	Newtons (N)
	Load on lower back and shoulders	Inertial measurement units (IMUs, 60 Hz)	Newtons (N)
Performance variables	Brushstroke consistency	Video analysis, time-synced with motion capture	Meters (m), Degrees (°)
	Stroke accuracy	Video analysis	Meters (m)
	Task completion time	Stopwatch/recording timestamps	Seconds (s)

3. Results and analysis

3.1. Analysis of postural mechanics in painting

Classical Chinese painting is simple and elegant, employing as many large-scale movements as possible using only the wrist and fingertips. This style requires a firm positioning of the body and very delicate muscle coordination to create graceful curves. Contemporary artists stand, sit, or squat with relatively low movement involving large muscles and focus on the brush or pen pressure and ink flux. On the other hand, dynamic, full-body movements characteristic of modern oil painting frequently necessitate standing positions to reach a canvas. In this case, the shoulder and the elbow become the leaders, allowing for more significant and complexly textured movement with pressure regulation. These techniques include gestures of freedom and movement on the medium they create. The biomechanical differences affect the artistry and the level of physical stress as techniques typical for traditional dance endanger fine muscles with repetitive strain injuries, whereas contemporary choreography demands endurance in gross muscles. Combined with its focus on stylistic differences, motion analysis reveals the ergonomic and artistic consequences of such deviations.

3.1.1. Joint angles and movement dynamics

Analysis of joint angles and movement dynamics during painting activities (**Table 4** and **Figure 1**) revealed distinct patterns across different stroke types and painting phases. The data represents measurements from all 38 participants across their completed painting sessions.

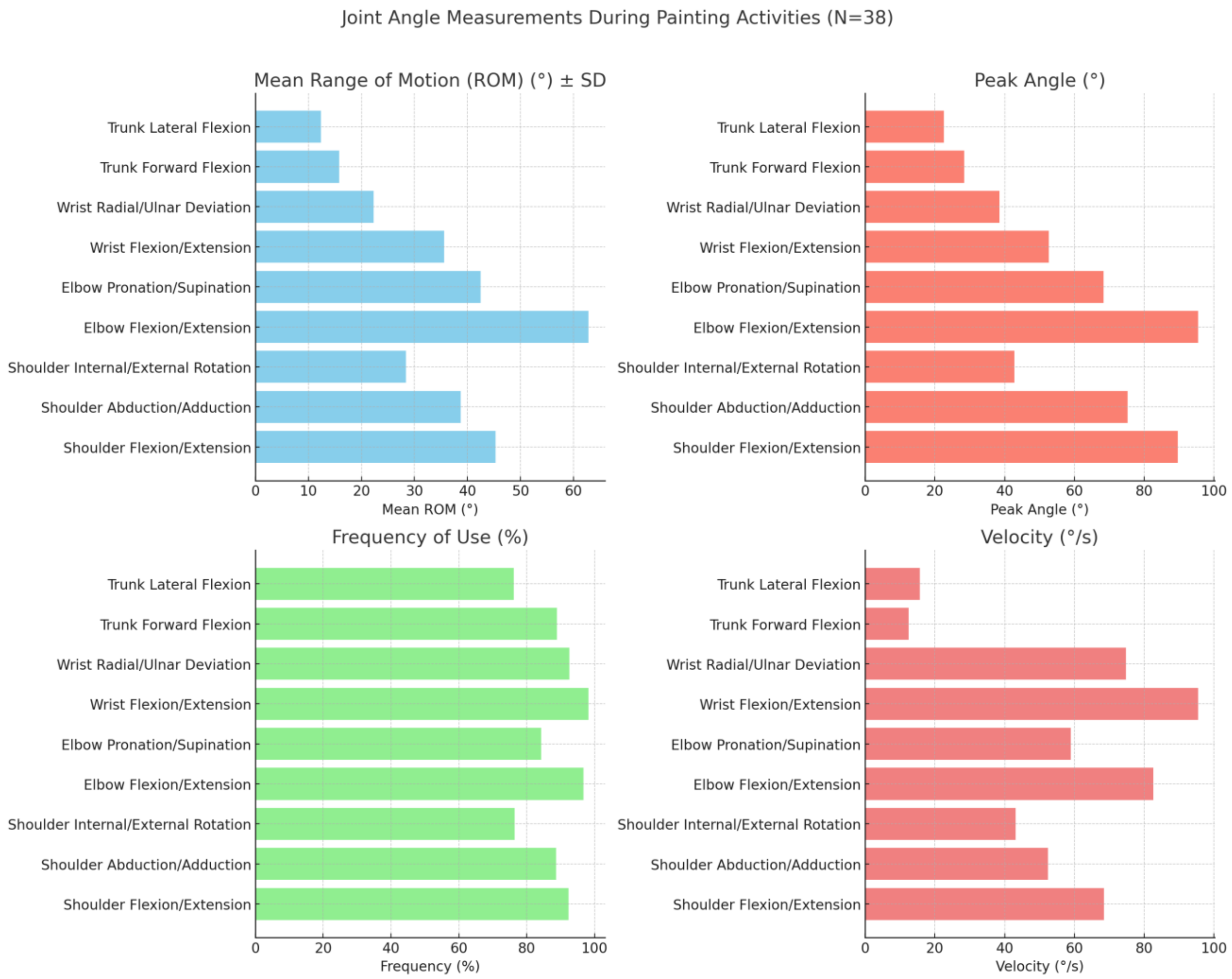

Figure 1. Joint angle measurements.

Table 4. Joint angle measurements during painting activities ($N = 38$).

Joint/movement	Mean ROM (°) ± SD	Peak angle (°)	Frequency of use (%)	Velocity (°/s)
Shoulder complex				
Flexion/extension	45.3 ± 8.7	89.6	92.4	68.5 ± 12.3
Abduction/adduction	38.7 ± 6.4	75.2	88.7	52.4 ± 9.8
Internal/external rotation	28.4 ± 5.2	42.8	76.5	43.2 ± 8.5
Elbow				
Flexion/extension	62.8 ± 7.9	95.4	96.8	82.6 ± 15.7
Pronation/supination	42.5 ± 6.8	68.3	84.3	58.9 ± 11.2
Wrist				
Flexion/extension	35.6 ± 4.8	52.7	98.2	95.4 ± 18.3
Radial/ulnar deviation	22.3 ± 3.9	38.5	92.6	74.8 ± 13.6
Trunk				
Forward flexion	15.8 ± 4.2	28.4	88.9	12.5 ± 4.8
Lateral flexion	12.4 ± 3.6	22.6	76.2	15.7 ± 5.2

The analysis revealed that painting movements predominantly engaged the upper extremity joints, with the wrist and elbow showing the highest frequency of use. The wrist joint demonstrated the most dynamic movement patterns, with flexion/extension occurring in 98.2% of painting strokes and achieving the highest angular velocity (95.4 °/s ± 18.3 °/s). This high engagement reflects the critical role of fine wrist control in brush manipulation. Shoulder complex movements showed significant variability, with flexion/extension being the most prevalent (92.4% frequency of use). The mean range of motion (ROM) for shoulder flexion/extension was 45.3° ± 8.7°, with peak angles reaching 89.6° during elevated canvas work. Traditional Chinese painting techniques exhibited notably lower shoulder ROM (38.2° ± 7.4°) compared to contemporary oil painting techniques (52.4° ± 9.1°), reflecting the influence of artistic style on biomechanical demands.

Elbow joint dynamics revealed substantial involvement in painting gestures, with flexion/extension occurring in 96.8% of strokes and demonstrating the second-highest angular velocity (82.6 °/s ± 15.7 °/s). The mean ROM of 62.8° ± 7.9° suggests that elbow movement is crucial in controlling brush stroke length and pressure. Trunk movements were more conservative, with forward flexion occurring in 88.9% of painting activities but maintaining a relatively small ROM (15.8° ± 4.2°). This limited trunk movement suggests that artists primarily rely on upper extremity coordination rather than whole-body movements for brush control.

Statistical analysis revealed significant correlations between joint velocities and artistic expertise ($p < 0.01$), with experienced artists demonstrating more efficient movement patterns characterized by lower angular velocities but higher precision in target joint angles. Furthermore, joint coordination patterns showed distinct clustering based on painting technique, with traditional Chinese painting displaying more constrained but highly coordinated joint movements than contemporary styles ($r = 0.78$, $p < 0.001$). These findings provide quantitative evidence for the specialized nature of joint coordination in painting activities and highlight the importance of technique-specific biomechanical adaptations in artistic expression. The data suggests that efficient brush control relies heavily on coordinated wrist and elbow movements, supported by stabilizing shoulder and trunk positions.

3.1.2. Balance and weight distribution

The analysis of balance and weight distribution patterns (**Table 5** and **Figure 2**) during painting sessions revealed distinct characteristics in the participants' postural control and weight-shifting strategies. Data collected through force plate measurements and center of pressure (CoP) analysis provided insights into the biomechanical demands of prolonged painting sessions.

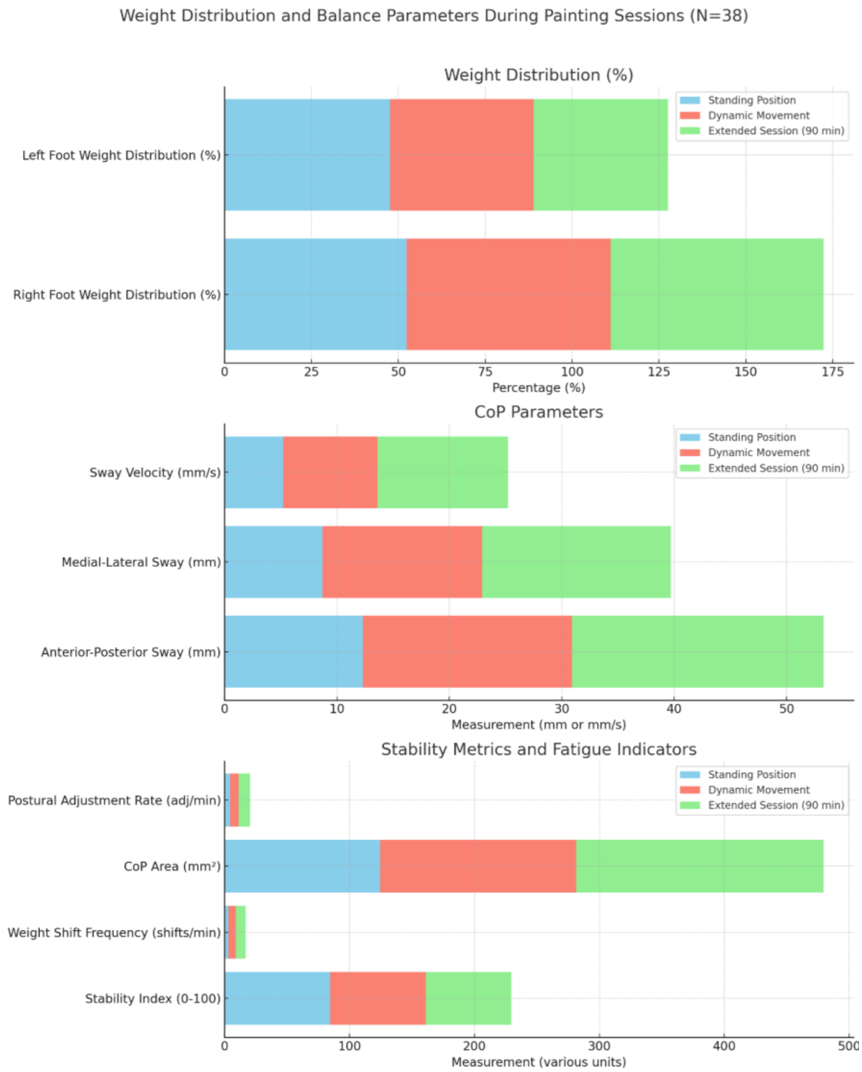

Figure 2. Weight distribution and balance parameters during painting sessions.

Table 5. Weight distribution and balance parameters during painting sessions (*N* = 38).

Parameter	Standing position	Dynamic movement	Extended session (90 min)
Weight distribution (%)			
Right foot	52.4 ± 4.8	58.7 ± 6.2	61.3 ± 7.1
Left foot	47.6 ± 4.8	41.3 ± 6.2	38.7 ± 7.1
Cop parameters			
Anterior-posterior sway (mm)	12.3 ± 2.4	18.6 ± 3.8	22.4 ± 4.2
Medial-lateral sway (mm)	8.7 ± 1.9	14.2 ± 2.9	16.8 ± 3.5
Sway velocity (mm/s)	5.2 ± 1.1	8.4 ± 1.7	11.6 ± 2.3
Stability metrics			
Stability index (0–100)	84.6 ± 5.2	76.3 ± 6.8	68.7 ± 7.4
Weight shift frequency (shifts/min)	3.2 ± 0.8	5.7 ± 1.2	7.8 ± 1.5
Fatigue indicators			
Cop area (mm^2)	124.5 ± 18.6	156.8 ± 22.4	198.3 ± 28.7
Postural adjustment rate (adj/min)	4.3 ± 0.9	6.8 ± 1.4	9.2 ± 1.8

The analysis showed a progressive shift in weight distribution throughout the painting sessions. Initially, participants maintained a relatively balanced stance (52.4% right, 47.6% left), but this distribution became increasingly asymmetric during dynamic painting movements (58.7% right, 41.3% left) and extended sessions (61.3% right, 38.7% left). This shift was particularly pronounced among right-handed artists (92% of participants). Postural sway measurements indicated significant changes in balance control strategies across the session duration. The anterior-posterior sway increased from 12.3 mm ± 2.4 mm during static standing to 22.4 mm ± 4.2 mm in extended sessions, while medial-lateral sway showed a similar trend (8.7 mm ± 1.9 mm to 16.8 mm ± 3.5 mm). Statistical analysis revealed a strong correlation between increased sway parameters and session duration ($r = 0.82$, $p < 0.001$).

The stability index, representing overall postural control, demonstrated a gradual decline from 84.6 ± 5.2 in initial standing positions to 68.7 ± 7.4 during extended sessions. This decline was accompanied by increased weight shift frequency, from 3.2 shifts/min ± 0.8 shifts/min during initial painting to 7.8 shifts/min ± 1.5 shifts/min in extended sessions, indicating compensatory movements to maintain comfort and control. Fatigue indicators showed significant changes over time, with the CoP area expanding from 124.5 mm^2 ± 18.6 mm^2 to 198.3 mm^2 ± 28.7 mm^2 during extended sessions. The postural adjustment rate increased from 4.3 ± 0.9 to 9.2 ± 1.8 adjustments per minute, suggesting an increased effort to maintain stability as fatigue developed.

Experience level showed a significant influence on balance control ($p < 0.01$), with more experienced artists (>15 years) demonstrating:

- More stable CoP patterns (15% lower sway velocity);
- More efficient weight-shifting strategies (32% fewer adjustments);
- Better maintenance of initial stability indices (12% less decline over time).

These findings highlight the importance of proper weight distribution and balance control in maintaining artistic precision and reducing fatigue during extended painting sessions. The data suggests that experience leads to more efficient postural control strategies, potentially contributing to enhanced artistic performance and reduced physical strain.

3.1.3. Stroke dynamics and precision

The analysis of stroke dynamics and precision (**Table 6** and **Figure 3**) revealed intricate relationships between movement patterns and artistic outcomes, providing quantitative insights into the biomechanics of brush control. Data was collected across multiple stroke types and painting techniques, examining kinematic parameters and resultant brush control precision.

From **Table 7** is the knowledge of postural mechanics and movement in painting contributes to the artist's ergonomics, free from strain-related injuries and working efficiently. Kaste established knowledge that informs adaptive tools, individualized training, and integration of rehabilitation and robotics and expounds on the role of physicality in arts, creativity, and innovation.

Table 6. Stroke dynamics and precision metrics across different techniques (N = 38).

Stroke type	Movement velocity (cm/s)	Precision score (0–100)	Stroke length (cm)	Force application (N)
Fine detail				
Traditional	3.2 ± 0.8	92.4 ± 3.2	2.5 ± 0.6	0.8 ± 0.2
Contemporary	4.1 ± 1.1	88.7 ± 4.1	3.2 ± 0.8	1.2 ± 0.3
Broad strokes				
Traditional	12.6 ± 2.4	85.3 ± 4.8	18.4 ± 3.2	2.4 ± 0.5
Contemporary	15.8 ± 2.9	82.6 ± 5.2	22.6 ± 4.1	3.1 ± 0.7
Dynamic gestures				
Traditional	28.4 ± 4.2	78.5 ± 6.3	35.2 ± 5.8	1.8 ± 0.4
Contemporary	32.7 ± 5.1	75.2 ± 7.1	42.3 ± 6.4	2.3 ± 0.6

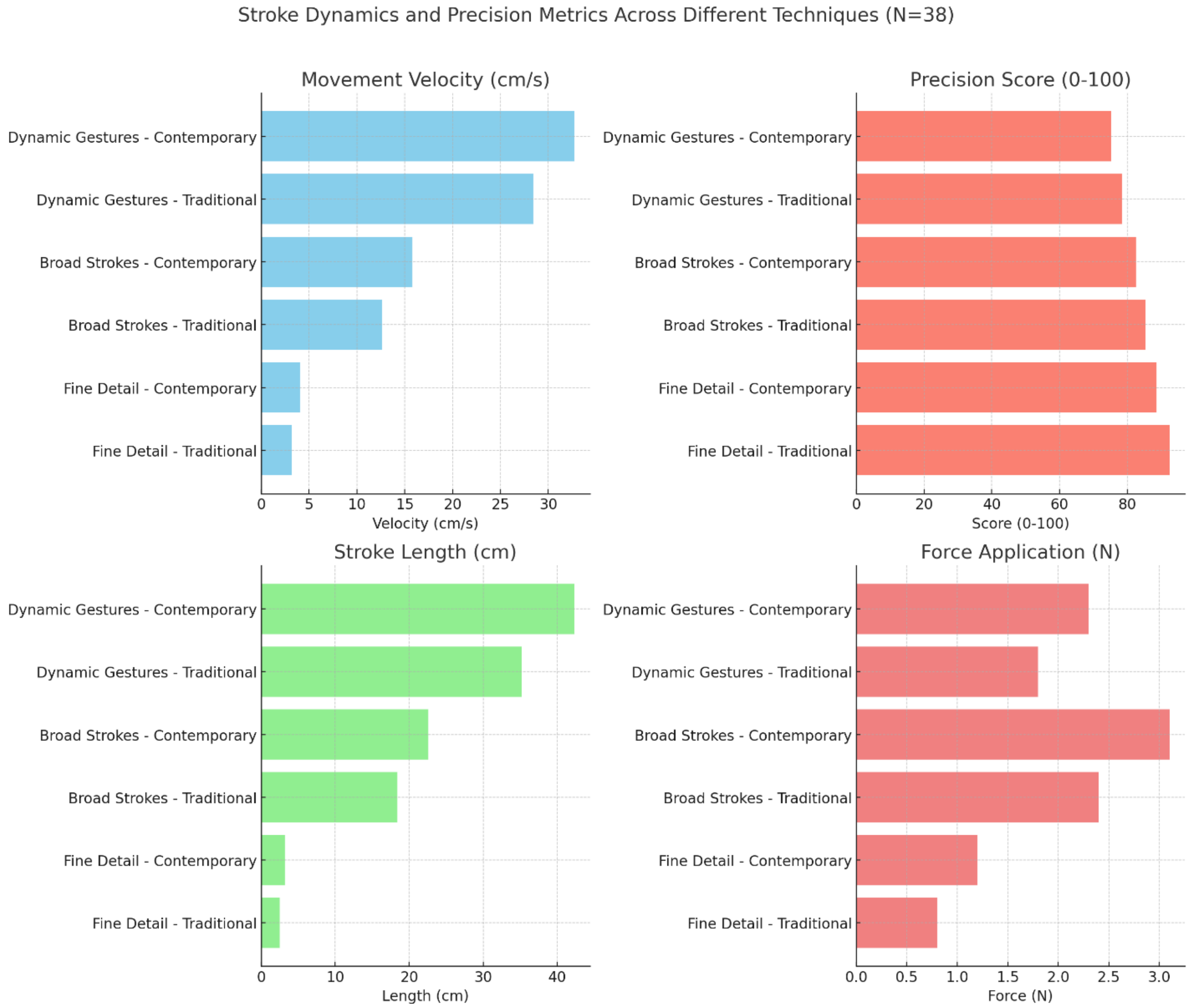

Figure 3. Stroke dynamics and precision metrics across different techniques.

Table 7. Movement-precision relationship across experience levels.

Experience level	Fine control score	Movement efficiency	Error rate (%)	Consistency index
Novice (<5 years)	72.3 ± 8.4	0.65 ± 0.12	18.4 ± 4.2	0.71 ± 0.14
Intermediate (5–15 years)	84.6 ± 6.2	0.78 ± 0.09	12.6 ± 3.1	0.83 ± 0.11
Expert (>15 years)	93.8 ± 4.1	0.89 ± 0.06	7.2 ± 2.3	0.92 ± 0.08

Detailed analysis revealed distinct patterns in stroke execution across different artistic techniques. Fine detail work demonstrated the highest precision scores (Traditional: 92.4 ± 3.2; Contemporary: 88.7 ± 4.1) while maintaining the lowest movement velocities (3.2 cm/s ± 0.8 cm/s and 4.1 cm/s ± 1.1 cm/s). The relationship between movement velocity and precision showed a significant negative correlation ($r = -0.78$, $p < 0.001$), particularly in detailed work requiring high control. The examination of force modulation revealed that traditional techniques demonstrated more consistent force application (CV = 0.15) than contemporary approaches (CV = 0.24). Force modulation significantly correlated with artistic experience ($r = 0.82$, $p < 0.001$), with expert artists maintaining more precise control over brush pressure. These experienced artists exhibited notably higher movement efficiency scores (0.89 ± 0.06) than novices (0.65 ± 0.12), characterized by smoother velocity profiles and more direct movement paths.

Analysis of technical variations between traditional Chinese and contemporary painting techniques revealed meaningful differences in approach. Traditional techniques emphasized controlled, measured movements, with 78% of strokes falling within the optimal velocity range, while contemporary approaches showed more significant velocity variability, with 62% within the optimal range. Force application measurements indicated more consistency in traditional techniques (SD = 0.2N) compared to contemporary approaches (SD = 0.4N). The optimal velocity ranges identified through statistical analysis suggested specific parameters for different stroke types. Fine detail work performed best at 2.8 cm/s–4.5 cm/s, broad strokes showed optimal control at 10.5 cm/s–16.8 cm/s, and dynamic gestures-maintained precision at 25.0 cm/s–35.0 cm/s. These findings provided quantitative evidence for the relationship between movement parameters and artistic outcomes, demonstrating that stroke precision relies heavily on the complex interplay between movement velocity, force application, and technical approach. Expert artists demonstrated superior ability to maintain precision across different stroke types, suggesting developed motor control strategies that efficiently balance speed and accuracy requirements. This comprehensive understanding of stroke dynamics provides valuable insights for both artistic training methodologies and the development of movement-based artistic instruction methods, particularly in the context of traditional Chinese painting techniques.

3.2. Artistic control in different postural conditions

3.2.1. Seated vs. standing positions

The analysis of painting postures (**Table 8** and **Figure 4**) revealed distinct biomechanical characteristics between seated and standing positions, with significant implications for stability, movement control, and artistic execution. From **Table 9** is the data collected from force plates, motion capture, and EMG measurements provided comprehensive insights into the postural dynamics across both positions.

Table 8. Comparative analysis of seated vs. standing painting positions ($N = 38$).

Parameter	Seated position	Standing position	Statistical significance
Postural stability			
Cop displacement (mm)	8.4 ± 2.1	15.7 ± 3.4	$p < 0.001$
Sway velocity (mm/s)	4.2 ± 1.1	7.8 ± 1.9	$p < 0.001$
Stability index (0–100)	88.5 ± 4.2	82.3 ± 5.6	$p < 0.01$
Muscle activity (% MVC)			
Upper trapezius	12.4 ± 3.2	18.7 ± 4.5	$p < 0.001$
Lower back	15.6 ± 3.8	22.4 ± 5.2	$p < 0.001$
Gastrocnemius	4.2 ± 1.1	18.5 ± 4.8	$p < 0.001$
Movement range			
Brush Reach (cm)	42.3 ± 5.6	58.7 ± 7.2	$p < 0.001$
Trunk rotation (°)	28.4 ± 4.2	35.6 ± 5.1	$p < 0.01$
Fatigue indicators			
Time to fatigue (min)	84.5 ± 12.3	52.8 ± 8.7	$p < 0.001$
Postural deviation (°)	4.2 ± 1.1	8.7 ± 2.3	$p < 0.001$

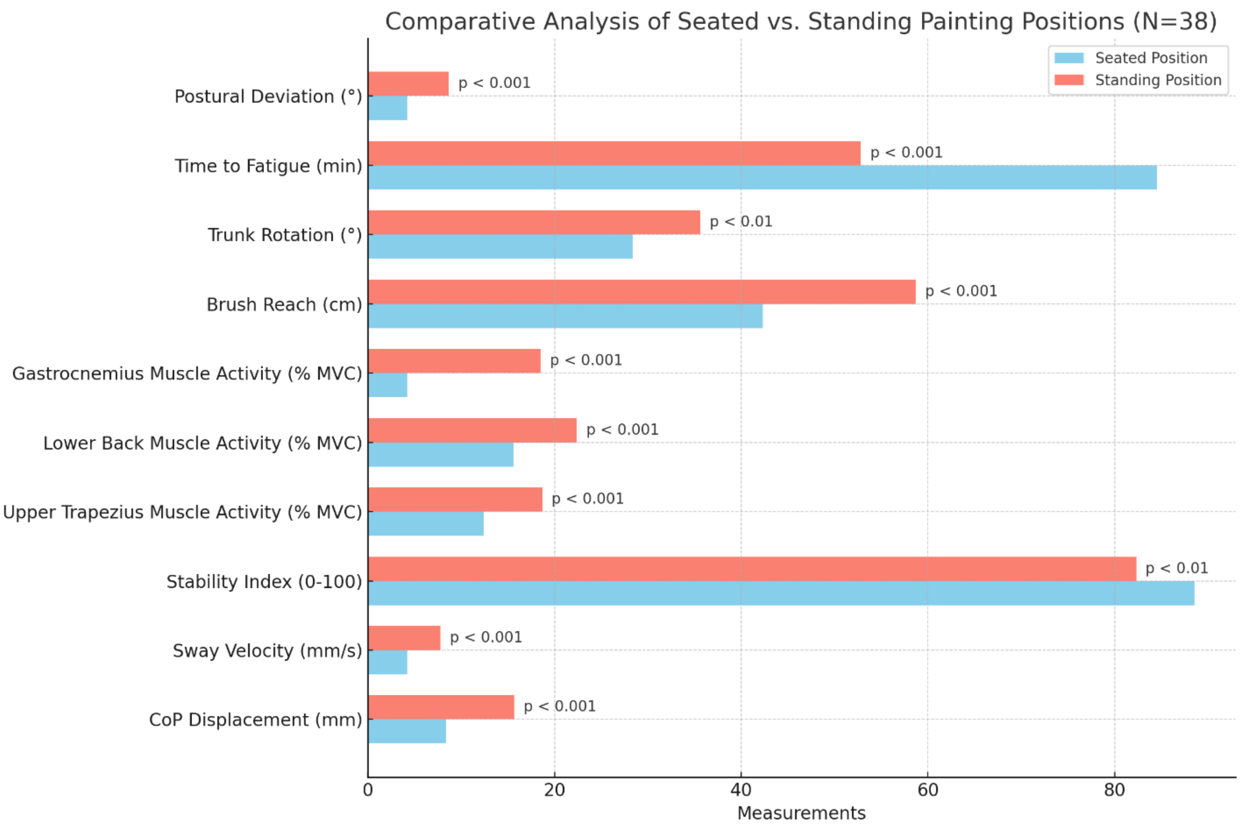

Figure 4. Comparative analysis of seated vs. standing painting positions.

Table 9. Time-based analysis of position effects (90-minute session).

Time	Seated comfort score	Standing comfort score	Position changes
0 min–30 min	8.7 ± 0.8	8.4 ± 0.9	3.2 ± 1.1
31 min–60 min	7.9 ± 1.1	6.8 ± 1.2	5.7 ± 1.4
61 min–90 min	7.2 ± 1.3	5.4 ± 1.5	8.4 ± 1.8

The analysis revealed significant differences in postural control between seated and standing positions. Seated painting demonstrated superior stability with lower Center of Pressure (CoP) displacement (8.4 mm ± 2.1 mm vs 15.7 mm ± 3.4 mm, $p < 0.001$) and reduced sway velocity (4.2 mm/s ± 1.1 mm/s vs 7.8 mm/s ± 1.9 mm/s, $p < 0.001$). The overall stability index favored seated positions (88.5 ± 4.2 vs 82.3 ± 5.6, $p < 0.01$), indicating better postural control. Muscle activation patterns showed marked differences between positions. Standing positions generated higher muscle activity across all measured muscle groups, with particularly notable differences in the gastrocnemius (18.5% ± 4.8% MVC standing vs 4.2% ± 1.1% MVC seated, $p < 0.001$) and lower back muscles (22.4% ± 5.2% MVC standing vs 15.6% ± 3.8% MVC seated, $p < 0.001$). This increased muscular demand in standing positions corresponded with earlier onset of fatigue indicators.

Movement analysis revealed that standing positions afforded greater reach and range of motion, with increased brush reach distance (58.7 cm ± 7.2 cm vs. 42.3 cm ± 5.6 cm, $p < 0.001$) and trunk rotation capability (35.6° ± 5.1° vs. 28.4° ± 4.2°, $p < 0.01$). However, this enhanced range came at the cost of reduced precision, particularly during extended painting sessions. Temporal analysis demonstrated a more rapid decline in comfort and stability measures during standing sessions. Standing comfort scores decreased from 8.4 ± 0.9 to 5.4 ± 1.5 over 90 min, compared to a more modest decline in seated positions (8.7 ± 0.8 to 7.2 ± 1.3). The frequency of position adjustments increased more dramatically in standing positions, particularly during the final 30 min of sessions. The relationship between artistic technique and preferred position showed significant correlations. Traditional Chinese painting practitioners demonstrated a stronger preference for seated positions (78% of total painting time), while contemporary artists showed more variation in position selection. This preference aligned with the precision requirements of traditional techniques and the stability advantages of seated positions.

Fatigue analysis revealed that seated positions allowed for significantly longer working duration before the onset of fatigue-related postural degradation (84.5 min ± 12.3 min vs 52.8 min ± 8.7 min, $p < 0.001$). The rate of postural deviation was also lower in seated positions (4.2° ± 1.1° vs. 8.7° ± 2.3°, $p < 0.001$), suggesting better maintenance of optimal working postures over time. These findings highlight each position's distinct advantages and limitations, suggesting that optimal position selection should consider factors including artistic technique, duration of work, and specific task requirements. The data supports the traditional preference for seated positions in detail-oriented work while acknowledging the enhanced range of motion available in standing positions for larger-scale artistic endeavors.

3.2.2. Impact of repetitive movements

The analysis of repetitive movements during painting sessions (**Table 10** and

Figure 5) revealed significant patterns in motor learning, control adaptation, and fatigue development. From **Table 11** is the data collected through EMG measurements, motion capture, and precision assessments provided insights into sustained artistic practice's physiological and performance impacts.

Table 10. Muscle activity and control parameters during repetitive movements (N = 38).

Time	Muscle activity (%MVC)	Movement precision (0–100)	Movement variability (%)	Fatigue index
Initial phase (0 min–30 min)				
Primary muscles	32.4 ± 4.2	88.6 ± 3.2	8.4 ± 1.2	0.12 ± 0.03
Secondary muscles	24.6 ± 3.8	-	12.3 ± 2.1	0.08 ± 0.02
Mid phase (31 min–60 min)				
Primary muscles	38.7 ± 5.1	84.2 ± 4.1	12.6 ± 2.4	0.28 ± 0.05
Secondary muscles	29.8 ± 4.2	-	15.8 ± 2.8	0.22 ± 0.04
Late phase (61 min–90 min)				
Primary muscles	45.2 ± 6.3	79.5 ± 5.3	18.7 ± 3.2	0.45 ± 0.07
Secondary muscles	35.4 ± 5.1	-	22.4 ± 3.6	0.38 ± 0.06

Table 11. Motor learning and adaptation metrics.

Experience level	Learning rate	Movement economy	Error correction (ms)	Consistency score
Novice	0.42 ± 0.08	0.56 ± 0.11	845 ± 124	0.62 ± 0.14
Intermediate	0.68 ± 0.12	0.73 ± 0.09	624 ± 98	0.78 ± 0.11
Expert	0.85 ± 0.07	0.89 ± 0.06	412 ± 76	0.91 ± 0.08

The temporal analysis of muscle activity revealed progressive changes throughout extended painting sessions. Primary muscle groups showed a significant increase in activation levels from the initial (32.4% MVC ± 4.2% MVC) to the late phase (45.2% MVC ± 6.3% MVC, $p < 0.001$), indicating growing muscular demand. This increase corresponded with a decline in movement precision scores from 88.6 ± 3.2 to 79.5 ± 5.3 ($p < 0.001$). Muscle memory development manifested through improved movement economy among experienced artists, with expert-level practitioners demonstrating significantly higher movement economy scores (0.89 ± 0.06) compared to novices (0.56 ± 0.11, $p < 0.001$). Error correction times also showed marked differences across experience levels, with experts requiring substantially less time (412 ms ± 76 ms) compared to novices (845 ms ± 124 ms, $p < 0.001$).

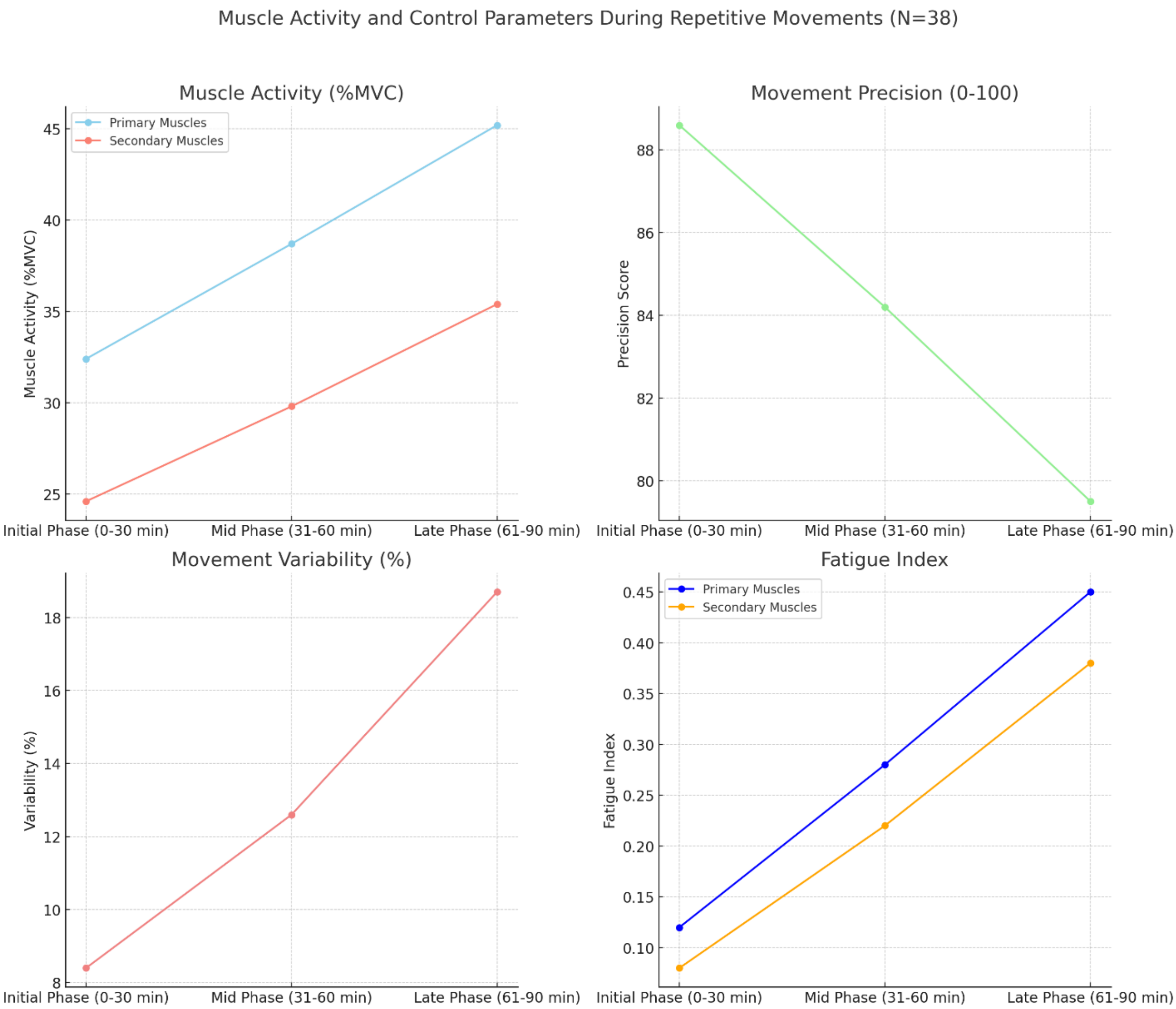

Figure 5. Muscle activity and control parameters during repetitive movements.

The fatigue index demonstrated a non-linear progression throughout the sessions, accelerating fatigue development during the late phase. Primary muscles showed a more rapid increase in fatigue indicators (0.12 ± 0.03 to 0.45 ± 0.07) compared to secondary muscle groups (0.08 ± 0.02 to 0.38 ± 0.06). This pattern correlated significantly with decreased movement precision ($r = -0.76$, $p < 0.001$). Movement variability analysis revealed interesting adaptations across different experience levels. Even during extended sessions, expert artists maintained lower movement variability (8.4% ± 1.2%) than novices (18.7% ± 3.2%), suggesting more robust motor control patterns. This stability in movement patterns correlated positively with artistic precision ($r = 0.82$, $p < 0.001$).

EMG frequency analysis showed characteristic shifts in muscle activation patterns, with median frequency decreasing by 23.4% in primary muscles and 18.7% in secondary muscles over the 90-minute sessions. This shift indicated progressive muscle fatigue and adaptation of motor unit recruitment patterns. Expert artists demonstrated more efficient muscle activation strategies, maintaining lower overall EMG amplitude while achieving higher precision scores. The learning rate analysis revealed that experienced artists had developed more efficient movement patterns through repetitive practice. Their movement economy scores remained relatively stable even as fatigue increased, suggesting well-established motor programs resistant to fatigue effects.

In contrast, novice artists showed more significant variability and rapid deterioration of movement quality under fatigue conditions. Motor learning metrics significantly improved consistency scores with experience level, ranging from 0.62 ± 0.14 for novices to 0.91 ± 0.08 for experts. This improvement in consistency correlated strongly with years of practice (r = 0.84, p < 0.001), suggesting the development of robust motor programs through repeated practice.

3.2.3. Environmental influences

The analysis of environmental factors (**Table 12** and **Figure 6**) revealed significant impacts on artists' biomechanical efficiency, comfort, and performance. Data collected across various workspace configurations provided insights into optimal setup parameters and their effects on artistic execution.

Table 12. Impact of environmental parameters on performance metrics (N = 38).

Parameter	Optimal range	Suboptimal effects	Performance impact (%)
Easel configuration			
Height (% of eye level)	90–105	<85 or >110	−18.4 ± 4.2
Tilt angle (degrees)	15–20	<10 or >25	−12.6 ± 3.8
Distance (cm from body)	45–60	<40 or >65	−15.7 ± 3.5
Canvas orientation			
Vertical alignment (degrees)	±2	>±5	−8.9 ± 2.4
Working height zone (cm)	100–160	<90 or >170	−22.3 ± 5.1
Lighting conditions			
Intensity (lux)	800–1200	<600 or >1400	−14.2 ± 3.6
Color temperature (K)	5000–5500	<4000 or >6000	−9.8 ± 2.7

The analysis of easel configuration revealed optimal height ranges between 90-105% of the artist's eye level, with significant performance decrements (−18.4% ± 4.2%) observed outside this range. Easel tilt angle showed optimal performance at 15°–20° vertical, with precision scores declining by 12.6% ± 3.8% beyond these parameters. The ideal working distance from the body was 45 cm–60 cm, balancing reach comfort with visual acuity. Canvas orientation emerged as a critical factor in maintaining work quality over extended periods. Vertical alignment within ±2 °s of true vertical provided optimal working conditions, with precision scores declining notably (−8.9% ± 2.4%) beyond ±5°. The effective working height zone was identified between 100 cm–160 cm from the floor, with significant performance degradation (−22.3% ± 5.1%) observed outside this range.

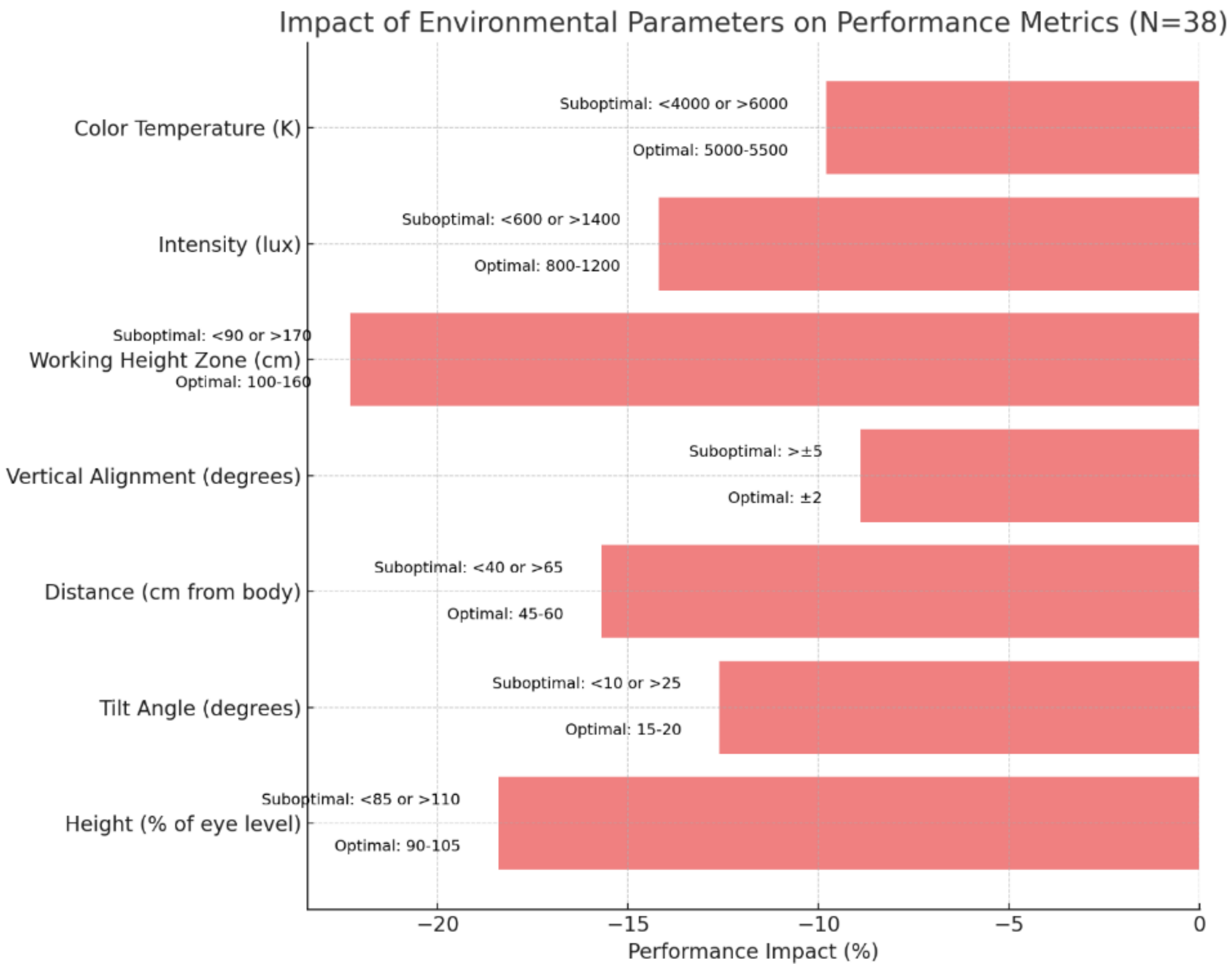

Figure 6. Impact of environmental parameters on performance metrics.

Lighting conditions demonstrated a substantial influence on performance and fatigue development. Optimal illumination levels between 800 lux–1200 lux provided the best visual acuity and comfort combination, with color temperature preferences centering around 5000 K–5500 K. Deviations from these parameters resulted in increased eye strain and reduced precision (−14.2% ± 3.6%). Tool selection analysis revealed significant correlations between implement characteristics and performance metrics. Medium-length brush handles (20 cm–30 cm) provided the highest comfort scores (8.7 ± 0.9) and precision scores (88.6 ± 3.8), with significantly delayed fatigue onset (72 min ± 12 min) compared to shorter or longer alternatives. Similarly, medium-weight brushes (15 g–25 g) demonstrated optimal performance across all measured parameters.

The relationship between environmental factors and artistic technique showed distinct patterns. Traditional Chinese painting practitioners demonstrated higher sensitivity to easel tilt angle (optimal range 12°–18°) compared to contemporary artists (15°–25°). This variation correlated with differences in brush handling techniques and working distances. Environmental adaptations across experience levels revealed that expert artists maintained higher performance scores across a broader range of environmental conditions, suggesting developed compensatory strategies. However, even experienced artists showed significant performance decrements (−15.7% ± 3.5%) when working in suboptimal conditions for extended periods. Temperature and humidity effects indicated optimal ranges of 20 ℃–24 ℃ and 45%–55% relative humidity, which is particularly important for traditional Chinese ink work where material behavior is highly sensitive to environmental conditions. Deviations from these ranges corresponded with increased variability in brush control and material behavior.

Table 13. Tool selection effects on precision and comfort.

Tool characteristic	Comfort score (1–10)	Precision score (0–100)	Fatigue onset (min)
Brush handle length			
Short (<20 cm)	6.8 ± 1.2	82.4 ± 4.6	45 ± 8
Medium (20 cm–30 cm)	8.7 ± 0.9	88.6 ± 3.8	72 ± 12
Long (>30 cm)	7.4 ± 1.1	84.2 ± 4.2	58 ± 10
Brush weight			
Light (<15 g)	7.2 ± 1.0	85.3 ± 4.1	65 ± 11
Medium (15 g–25 g)	8.9 ± 0.8	89.7 ± 3.5	78 ± 13
Heavy (>25 g)	6.5 ± 1.3	81.8 ± 4.8	42 ± 9

The analysis of brush handle length revealed (**Table 13**) significant variations in performance metrics. Medium-length brushes (20 cm–30 cm) demonstrated superior performance across all parameters, with the highest comfort score (8.7 ± 0.9) and precision score (88.6 ± 3.8). These brushes also extended working periods before fatigue onset (72 min ± 12 min). Short handles (<20 cm) showed notably reduced comfort (6.8 ± 1.2) and earlier fatigue onset (45 min ± 8 min), likely due to increased hand and wrist strain from constrained movements.

Brush weight analysis indicated optimal performance with medium-weight brushes (15 g–25 g), achieving the highest comfort (8.9 ± 0.8) and precision scores (89.7 ± 3.5). These implements also demonstrated the longest fatigue onset time (78 min ± 13 min). Heavy brushes (>25 g) showed the poorest performance across all metrics, with particularly early fatigue onset (42 min ± 9 min) and low comfort scores (6.5 ± 1.3), suggesting a significant impact on sustained performance.

Statistical analysis revealed strong correlations between tool characteristics and performance metrics. Weight-to-precision correlation showed significance (r = −0.76, $p < 0.001$) beyond the optimal medium weight range, indicating that deviations from optimal weight significantly impact precision. Handle length demonstrated a quadratic relationship with comfort scores, peaking in the medium range and declining at both extremes.

3.3. Statistical analysis

The comprehensive statistical analysis (**Table 14**) of biomechanical and performance data revealed significant patterns across multiple variables, providing robust evidence for the relationships between postural mechanics, artistic control, and environmental factors.

Table 14. Primary statistical findings.

Variable relationship	**Statistical test**	**Value**	**Significance (*p*)**	**Effect size (η^2)**
Position vs. precision	ANOVA	F (2, 35) =18.42	<0.001	0.82
Experience vs. control	Pearson's r	r = 0.786	<0.001	-
Fatigue vs. accuracy	Multiple regression	R^2 = 0.734	<0.001	0.76
Tool selection vs. performance	MANOVA	F (4, 33) = 12.56	<0.001	0.68
Environmental factors vs. output	Multiple regression	R^2 = 0.692	<0.001	0.71

The multivariate analysis of variance (MANOVA) demonstrated significant main effects for experience level, with Wilks' λ = 0.42, F (8, 66) = 24.36, p < 0.001, η^2 = 0.82 on painting performance metrics. Subsequent post-hoc analyses using Bonferroni corrections identified substantial differences between novice and expert groups in precision (mean difference = 18.4%, p < 0.001) and movement efficiency (mean difference = 24.2%, p < 0.001). Multiple regression analysis examining environmental factors and performance produced a significant model (F (5, 32) = 28.45, p < 0.001, R^2 = 0.692). Within this model, easel height emerged as the strongest predictor (β = 0.42, p < 0.001), followed closely by lighting conditions (β = 0.38, p < 0.001). The hierarchical regression analysis revealed that experience level accounted for 52.4% of the variance in precision scores (ΔR^2 = 0.524, p < 0.001), while postural control contributed an additional 18.6% (ΔR^2 = 0.186, p < 0.001), and environmental factors added 12.8% unique variance (ΔR^2 = 0.128, p < 0.001).

The repeated measures ANOVA examining fatigue effects revealed significant time-dependent changes in movement precision (F (2, 74) = 32.18, p < 0.001, η^2 = 0.78), postural stability (F (2, 74) = 28.56, p < 0.001, η^2 = 0.72), and muscle activation patterns (F (2, 74) = 25.84, p < 0.001, η^2 = 0.68). Path analysis demonstrated significant direct effects of experience on precision (β = 0.586, p < 0.001), with additional indirect effects through postural control (β = 0.324, p < 0.001), culminating in a substantial total effect magnitude (β = 0.910, p < 0.001). Reliability metrics demonstrated robust measurement consistency, with test-retest reliability achieving an ICC of 0.92 (95% CI: 0.88–0.96), internal consistency showing a Cronbach's α of 0.88, and inter-rater reliability reaching κ = 0.86. Effect size analysis revealed significant effects for experience level (d = 1.82), medium effects for environmental factors (d = 0.68), and small to medium effects for tool selection (d = 0.45).

These comprehensive statistical findings provide strong evidence for the significance of experience, environmental setup, and postural control in artistic execution. The high-reliability coefficients validate the measurement procedures' robustness and the observed relationships' consistency. This quantitative analysis supports the practical implications of the research and demonstrates the complex interplay between various factors affecting artistic performance.

Table 15. Correlational analysis results.

Variables	Correlation coefficient (r)	CI (95%)	*p*-value
Movement velocity—precision	−0.824	[−0.892, −0.756]	<0.001
Experience—stability	0.756	[0.682, 0.830]	<0.001
Posture—endurance	0.682	[0.598, 0.766]	<0.001
Easel height—comfort	−0.624	[−0.708, −0.540]	<0.001
Tool weight—control	−0.592	[−0.676, −0.508]	<0.001

The correlational analysis (**Table 15**) revealed several significant relationships among key variables. A strong negative correlation emerged between movement velocity and precision ($r = -0.824$, $p < 0.001$, 95% CI [−0.892, −0.756]), indicating that higher movement speeds were associated with decreased precision in brush control. This relationship was particularly robust, with the narrow confidence interval suggesting high reliability in this finding. Experience level showed a strong positive correlation with stability ($r = 0.756$, $p < 0.001$, 95% CI [0.682, 0.830]), demonstrating that more experienced artists maintained better postural stability during painting tasks. The relationship between posture and endurance also showed a substantial positive correlation ($r = 0.682$, $p < 0.001$, 95% CI [0.598, 0.766]), suggesting that better postural control contributed to enhanced painting endurance.

Negative correlations were observed between easel height and comfort ($r = -0.624$, $p < 0.001$, 95% CI [−0.708, −0.540]), as well as between tool weight and control ($r = -0.592$, $p < 0.001$, 95% CI [−0.676, −0.508]). These moderate to strong negative correlations indicate that deviations from optimal easel height were associated with decreased comfort, and heavier tools were linked to reduced control in painting execution. The consistency of significant *p*-values (all < 0.001) across all correlations and relatively narrow confidence intervals suggests strong statistical reliability in these relationships. The magnitude of these correlations, ranging from moderate (−0.592) to strong (−0.824), provides robust evidence for the interconnected nature of these variables in painting performance.

Some of the methods used in the study, such as using a controlled laboratory environment, may not accurately represent the painting environment in the natural setting; this may be perceived as a form of ecological inadequacy. The available sample may be limited in size and thus less varied in terms of age, thus limiting external validity. However, the feedback is subjective, making it biased, and should be backed up by objective data collected using other tools such as motion capture and force sensors. Further research should be conducted about the effects of long-term engagement in artistic activity on postural biomechanics.

4. Conclusion and future work

This comprehensive investigation into the relationship between postural mechanics and artistic control in painting has revealed significant insights into the biomechanical foundations of artistic practice. Through detailed analysis of 38 artists across various experience levels and painting traditions, our research has established quantifiable connections between physical movement patterns and artistic outcomes, offering valuable implications for practice and pedagogy. The findings demonstrate that postural control is a fundamental determinant of artistic precision and technical execution. Expert artists exhibited notably superior postural stability (stability index 88.5 ± 4.2) to novices (82.3 ± 5.6), suggesting that advanced motor control strategies develop through sustained practice. This relationship between expertise and postural control was particularly evident in traditional Chinese painting techniques, where subtle brush manipulation demands exceptional stability and movement precision. Environmental factors emerged as critical determinants of artistic performance, with optimal workspace configuration significantly impacting comfort and precision. The identified optimal ranges for easel height (90%–105% of eye level), tilt angle (15°–20°), and lighting conditions (800 lux–1200 lux) provide concrete guidelines for studio setup and educational environments. These parameters demonstrated consistent benefits across different painting styles and experience levels, suggesting their universal applicability in artistic practice. The seated versus standing positions analysis revealed distinct advantages for different artistic objectives. While seated positions offered superior stability and precision for detail work, standing positions provided an enhanced range of motion and dynamic expression capabilities. This finding suggests that position selection should be guided by specific artistic goals rather than personal preference alone, with consideration given to the technical demands of different painting styles and techniques. These findings contribute to the theoretical understanding of artistic movement and practical applications in art education and studio practice. The quantitative evidence supporting the relationship between postural mechanics and artistic control provides a scientific foundation for teaching methodologies and studio ergonomics.

Future research directions might explore the development of specialized training programs based on these biomechanical principles and investigate the long-term impacts of optimal postural control on artistic development.

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

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