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Research on optimization of piano playing skills and sports injury prevention based on biomechanical analysis

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Abstract In this study, the activity patterns of hand muscles, joint trajectories and finger force application characteristics during piano playing were systematically analyzed by combining biomechanical methods. Using a Vicon 3D motion capture system, Delsys electromyography (EMG) equipment, a high frame rate video camera, and a Tekscan pressure sensor, the movement characteristics and muscle loads of 10 piano players were measured under different playing techniques (such as legato, staccato, arpeggio, octave continuo, and chordal playing). The results of the study showed that different playing techniques had a significant effect on the activation level and force application pattern of the hand muscles. Octave legato and monophonic breaks resulted in the largest finger trajectories and highest peak velocities, which significantly increased the activation levels of EMG signals to the finger flexors and wrist flexors, potentially leading to muscle fatigue and risk of injury. Monophonic legato and arpeggio, on the other hand, had more stable trajectories and lower EMG activation levels, making them suitable for prolonged performance. The force distribution analysis showed that the highest finger forces were applied in octave legato and monophonic breaks, and that chord playing requires a balanced application of finger forces to ensure tonal stability.

Index Terms biomechanics, piano performance, finger trajectories, electromyography (EMG), force distribution, motion capture, muscle fatigue, performance technique optimization

I. Introduction

In the context of today's rapid development of digitization and intelligence, high-dimensional data analysis techniques have been widely used in various fields, including several cross-disciplinary disciplines such as music recommender systems, sports science and biomechanics[1], [2]. Biomechanics (biomechanics), as a discipline that studies the movement of living organisms and their mechanical mechanisms, has been playing an increasingly important role in recent years in the field of music performance, especially piano performance[3], [4]. Piano performance is a highly refined movement process, involving the coordinated control of fingers, wrists, forearms, shoulders, and even the whole body, and at the same time, it is affected by a variety of factors, such as nervous system regulation, muscle mechanical properties, and exercise habits. Through biomechanical analysis, it is possible to understand how players optimize their playing skills by using factors such as muscle strength, joint angles, and movement patterns to improve accuracy and stability, and reduce the risk of sports injuries[5], [6].

In high-level piano playing, the independence of the fingers, the rational distribution of power, and the coherence of movement are crucial. Performers need to complete complex fingering changes within a short period of time, and control changes in strength and timbre while maintaining rhythmic stability[7]. Biomechanical studies have shown that the activation patterns of hand muscles during playing are similar to the muscle synergy patterns of athletes performing fine motor tasks (e.g., fencing, archery, etc.). This suggests that piano players can draw on the findings of sports biomechanics to optimize muscle control strategies through training to enhance performance[8], [9]. For example, a rational distribution of forces between finger and forearm muscles can reduce the burden on individual muscle groups and improve flexibility and durability of playing. In addition, it was found that piano playing proficiency is closely related to neuromuscular adaptation, and long-term practice not only improves playing skills, but also promotes fine control of hand movements in the motor cortex of the brain[10].

On the other hand, biomechanics can also provide piano players with scientific strategies for preventing sports injuries. Many professional pianists suffer from Repetitive Strain Injury (RSI), tenosynovitis, carpal tunnel syndrome and other disorders after a long period of playing, and these problems often originate from the overuse of wrist, finger and forearm muscles[11], [12]. Through biomechanical modeling, it is possible to analyze the stresses on the joints during performance, identify high-risk movement patterns that can easily lead to injury, and propose adjustments accordingly. For example, if the finger muscles bear excessive pressure during the performance of certain difficult sections, the angle of the wrist joint can be adjusted to share the force and reduce local muscle fatigue[13]. Further, based on data mining technology and high-dimensional data analysis methods, a personalized piano playing motion analysis system can be constructed to monitor the movement patterns of players in real time and provide accurate feedback to help them optimize their playing skills and reduce the risk of injury[14].

This study aims to combine high-dimensional data collaborative filtering recommendation algorithms with biomechanical analysis methods to optimize the analysis of hand movements during piano playing. By constructing a dataset based on large-scale musical works and using collaborative filtering methods to analyze the playing styles and technical preferences of players, we can achieve personalized recommendation of playing habits[15]. At the same time, combined with biomechanical modeling, we are able to evaluate the effects of different playing styles on hand muscle loading, and provide more scientific performance training programs for piano players. Ultimately, this study hopes to provide new theoretical support and practical guidance for piano performance teaching, player health management, and optimization of intelligent music recommendation systems through a multidisciplinary approach.

II. Optimization Analysis of Biomechanics and Piano Playing Technique

Piano playing is a highly complex motor skill involving coordinated control of the fingers, wrists, forearms, shoulders and even the whole body. Its core lies in the fine motor ability of the hand, muscle power distribution, joint stability and the control ability of the nervous system. Biomechanics (Biomechanics), as a discipline that studies the laws of motion and mechanical mechanisms of living organisms, provides a scientific basis for the optimization of piano playing skills[16]. This chapter combines high-dimensional data analysis techniques to study the biomechanical characteristics of piano players' hand movements, and uses data mining methods to analyze the relationship between finger forces, joint angles, muscle activation patterns and playing techniques, so as to optimize playing strategies and reduce the risk of injury.

II. A.Kinematic analysis of piano playing

During piano playing, the fingers, wrist, and forearm form a kinematic chain with multiple degrees of freedom. Finger movements can be categorized into the coordinated movements of the following three main joints: Distal Interphalangeal Joint (DIP); Proximal Interphalangeal Joint (PIP); Metacarpophalangeal Joint (MCP); and Metacarpophalangeal Joint (MCP). (MCP, Metacarpophalangeal Joint)

Let θ_{DIP}, θ_{PIP}, θ_{MCP} be the angles of the corresponding joints, then the kinematic model of the finger can be expressed as:

$$\begin{aligned} X &= L_1 \cos\theta_{MCP} + L_2 \cos(\theta_{MCP}+\theta_{PIP}) + L_3 \cos(\theta_{MCP}+\theta_{PIP}+\theta_{DIP}) \\ Y &= L_1 \sin\theta_{MCP} + L_2 \sin(\theta_{MCP}+\theta_{PIP}) + L_3 \sin(\theta_{MCP}+\theta_{PIP}+\theta_{DIP}) \end{aligned} \quad (1)$$

where L_1, L_2, L_3 are the length of the knuckle and (X,Y) are the coordinates of the fingertip respectively.

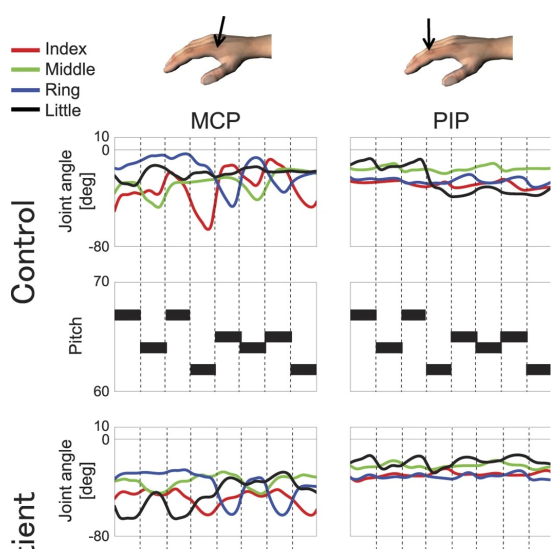

Figure 1: Plot of finger movement trajectory and joint angle change

Figure 1 shows the trajectories of the fingers before, during and after keystrokes during piano playing, and also analyzes the angular changes of the interphalangeal joints (DIP, PIP, MCP) and wrist joints[17]. The trajectory curves can intuitively reflect the effects of different playing styles (e.g. legato, staccato) on hand biomechanics. The trajectories reflect the biomechanical adaptations of different playing techniques (e.g., rapid arpeggio, octave legato) on the fingers.

The angle of the wrist θ_w and the angle of the forearm $\left(\theta_f\right)$ affect the force and stability of the fingers. By adjusting θ_w and $\left(\theta_f\right)$, the player controls the force of keystrokes, optimizes muscle load, and reduces fatigue.

$$F_{\text{key}} = M_{\text{hand}} g + M_{\text{forearm}} g \cos\left(\theta_f\right) \tag{2}$$

where F_{key} is the force of the fingers acting on the keys, Mhand and M_{forearm} are the hand and forearm masses, respectively, and gg is the acceleration due to gravity.

II. B.Dynamics Analysis of Piano Performance

In piano playing, the force applied to the fingers needs to consider the joint torque and muscle force. Let τ_{MCP}, τ_{PIP} , τ_{DIP} be the torque of each joint, then the dynamic equations are as follows:

$$I_{MCP}\ddot{\theta}_{MCP} + C_{MCP}\dot{\theta}_{MCP} + K_{MCP}\theta_{MCP} = \tau_{MCP} \tag{3}$$

$$I_{PIP}\ddot{\theta}_{PIP} + C_{PIP}\dot{\theta}_{PIP} + K_{PIP}\theta_{PIP} = \tau_{PIP} \tag{4}$$

$$I_{DIP}\ddot{\theta}_{DIP} + C_{DIP}\dot{\theta}_{DIP} + K_{DIP}\theta_{DIP} = \tau_{DIP} \tag{5}$$

where I is the moment of inertia, C is the damping coefficient, and K is the stiffness coefficient.

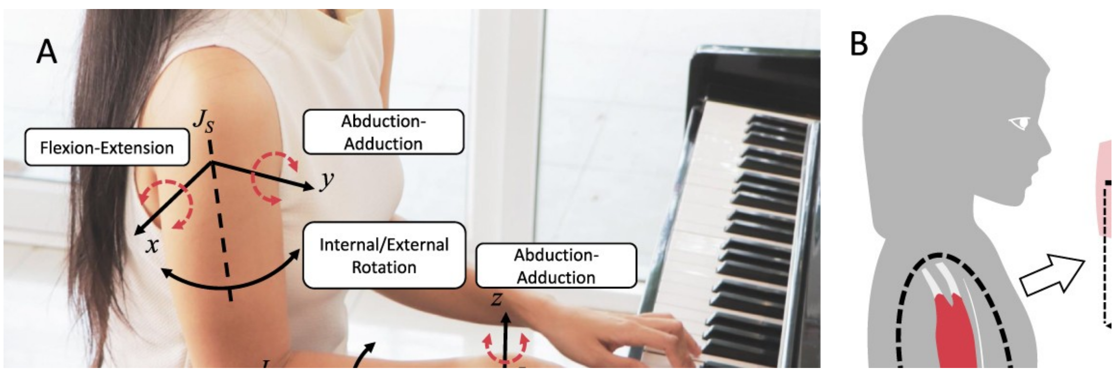

Figure 2: Mechanical modeling of piano keystrokes

Figure 2 constructs a mechanical model of the finger, key, and spring-damping system. By analyzing the speed of finger keystrokes, the applied force, and the key reaction force, the hand muscle exertion can be optimized to reduce fatigue and improve playing stability. By adjusting the magnitude and direction of the keystroke force, unnecessary muscle tension is reduced and playing efficiency is improved[18].

Fingers are primarily driven by the Flexor and Extensor muscles, which work in tandem to achieve precise keystrokes.

$$F_{\text{flexor}} = K_{\text{flexor}}\left(\theta_{\text{target}} - \theta_{\text{current}}\right) - C_{\text{flexor}}\dot{\theta} \tag{6}$$

$$F_{\text{extensor}} = K_{\text{extensor}}\left(\theta_{\text{target}} - \theta_{\text{current}}\right) - C_{\text{extensor}}\dot{\theta} \tag{7}$$

where K and C denote the muscle stiffness and damping coefficient, respectively, and θ_{target} is the target angle.

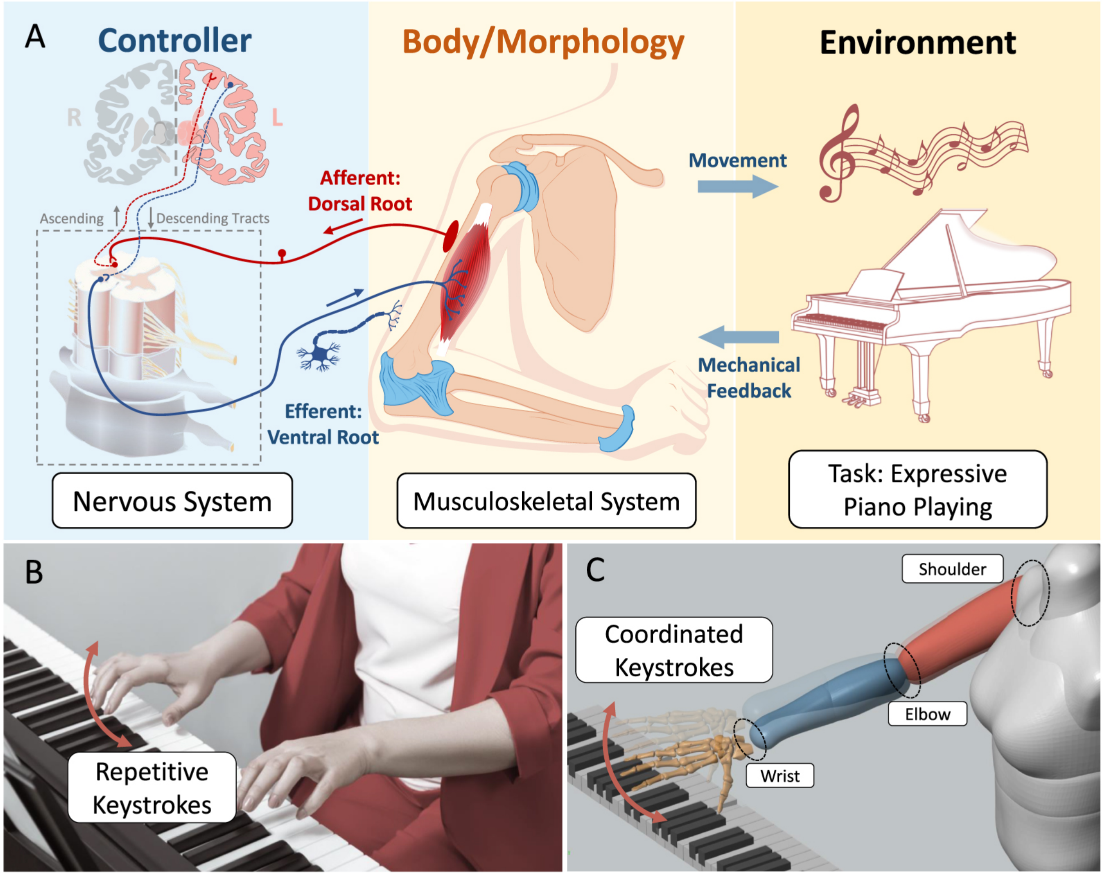

Figure 3: Hand Muscle Groups and Stress Distributions

Figure 3 shows the activation of the pianist's hand muscles and the stress distribution under different playing techniques (e.g., fast running, double-tonguing, strong playing). It shows the degree of involvement of major muscles (e.g., flexors, extensors, and wrist flexors) during different finger movements. Based on the EMG data, personalized training programs can be developed to enhance playing flexibility and endurance.

III. Architecture

The computerized evaluation system for piano performance is an automated system designed to analyze and assess a pianist's performance. It identifies the played musical piece, evaluates whether it aligns with established performance standards and musical logic, and assigns a score based on predefined criteria.

In future iterations, the system will be enhanced to provide detailed textual feedback, offering performers specific suggestions for improvement. This advancement aims to refine the evaluation process by integrating more nuanced analysis and personalized recommendations.

The computerized evaluation system for piano performance is an automated system designed to analyze and assess a pianist's performance. It identifies the played musical piece, evaluates whether it aligns with established performance standards and musical logic, and assigns a score based on predefined criteria. The overall framework of the proposed system is illustrated in Figure 4.

Figure 4 illustrates the overall structure of the computerized evaluation system for piano performance, which integrates multiple components to provide an accurate assessment of a pianist's performance. The system consists of several core modules, including data acquisition, preprocessing, feature extraction, performance analysis, and feedback generation. The data acquisition module captures audio signals and biomechanical movement data from the pianist, ensuring that both musical and physical performance factors are considered. The preprocessing module filters noise and standardizes input data for accurate analysis. Feature extraction identifies key attributes such as note timing, intensity, articulation, and biomechanical parameters. The performance analysis module evaluates technical proficiency and biomechanical efficiency based on predefined benchmarks. Finally, the feedback generation module provides detailed recommendations to help performers optimize their technique and reduce injury risks. By integrating biomechanics and high-dimensional data analysis, this system aims to enhance both artistic expression and physical well-being in piano performance.

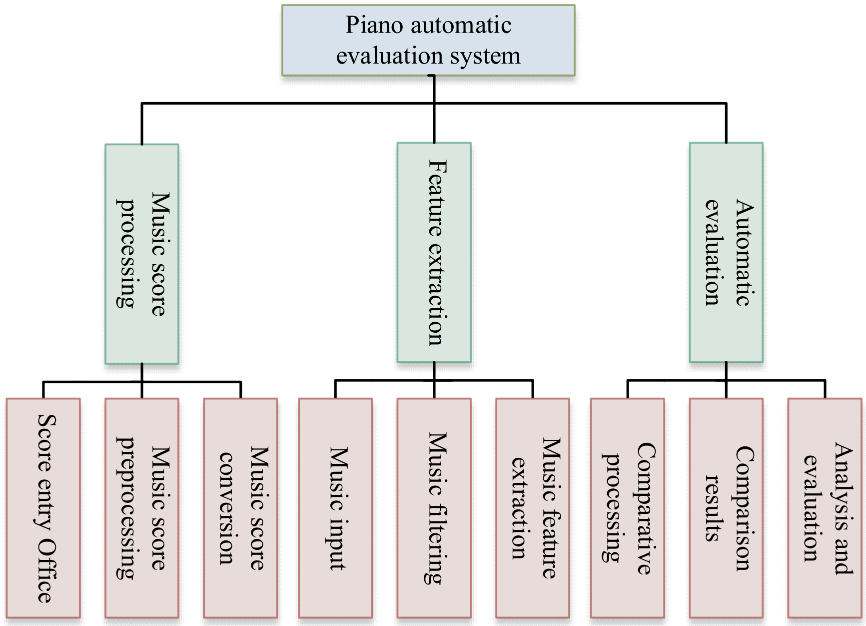

Figure 4: The overall structure of the system

The method used to identify the beginning frame and the end frame in piano music is comparable. The method guarantees precise segmentation by examining temporal patterns and acoustic characteristics, which is essential for performance assessment and additional research.

IV. Overview of recommendation algorithms for collaborative filtering on high-dimensional data

The spatial vector approach is mostly used to establish the weight values between data points while assessing the similarity of high-dimensional data. Based on the weight data, a suitable threshold is established to guarantee the accuracy of the similarity assessment. This prevents excessively high weight values, which could lead to lower similarity scores. The weight calculation formula for high-dimensional data is as follows:

$$\text{Weight }(t)_d = \left[\alpha(\text{t})_\text{d} + \beta(\text{t})_\text{d}\right] \times \text{TFIDF(t)} \tag{8}$$

$$\text{TFIDF}(t)_d = \frac{\text{TF}(t)_d \times \log 10\left(\frac{N_k}{n_i} + 0.01\right)}{\sqrt{\sum_{xd}\left[TF(t)_d \times \log 10\left(\frac{N_k}{n_i} + 0.01\right)\right]^2}} \tag{9}$$

In the above equation, N_k indicates how many characteristics there are in the high-dimensional data information set. $TF(t)_d$ indicates the likelihood that high-dimensional data t will exist in dataset d, n_i denotes the number of all high-dimensional data in dataset d.

According to adaptive analysis technique 0, high-dimensional data similarity is defined as follows:

$$\text{Sim}\left(s_i, s_j\right) = \frac{\left|C_i \cap C_j\right|}{\left|C_i \cup C_j\right|} \tag{10}$$

In the above equation, C represents the set of feature information for high-dimensional data. By computing the feature vectors ss and s', the contrast value between them is obtained, allowing the determination of similarity.

Equation (10) defines the similarity measure, where a value of 0 indicates no similarity, while 1 signifies complete similarity between the high-dimensional data[19].

It is possible to determine the distribution of various high-dimensional data points within the collection by examining the similarity. This distribution is represented by the following matrix:

The following is an expression for the high-dimensional data I's score result on target data J: For collaborative filtering of high-dimensional data, m is the number of rows and n is the number of columns of the scoring matrix R_{ij}. The assessment level of the high-dimensional data is expressed by a constant between 0 and 5, which stands for the rating of the collaborative filtering of the high-dimensional data.

$$P(c_k) = \sum_{i=1}^{N} \frac{I(c_k)}{N} \tag{11}$$

$$P\left(q_i^i \mid c_k\right) = \frac{\sum_{i=1}^{N} I\left(q_i^j, c_k\right)}{\sum_{i=1}^{N} I(c_k)} \tag{12}$$

where N represents the number of times users click on preferences, $I(c_k)$ indicates the likelihood that users' search results and ratings will coincide, and $I\left(q_i^j, c_k\right)$ denotes the conditional probability of users' search $\sum_{i=1}^{N} I(c_k)$ indicates the likelihood that the training samples and user preferences will be comparable when high-dimensional data is filtered collaboratively. Once the model has been trained, the high-dimensional data can be subjected to collaborative filtering inference q^j:

$$U = P(c_k) \prod_{j=1}^{n} P\left(q_i^j \mid c_k\right) \tag{13}$$

In the above equation, varying user preferences are determined based on the characteristics of the high-dimensional data. This value reflects the connection between user preferences and the resulting recommendations.

V. Results

V. A. Analysis of Piano Playing Technique Based on Biomechanics

V. A. 1) Experimental purpose

The purpose of this experiment is to analyze the activity patterns of hand muscles, joint trajectories and finger force application characteristics during piano performance through biomechanical methods in order to optimize the piano playing techniques. Motion capture technology, electromyography (EMG) measurements and high-precision pressure sensors were used to explore the effects of different playing techniques (e.g. legato, staccato, arpeggio, etc.) on the hand muscle groups and joint loads, which can help players to improve their performance efficiency and reduce the risk of sports injuries.

V. A. 2) Experimental methodology

Ten piano players were selected for this experiment, consisting of five professional players (≥10 years of experience) and five amateur players (≤5 years of experience). Subjects were all right-hand dominant with no history of muscle disease or hand injury.

Equipment and tools included a Vicon 3D Motion Capture System: used to record finger and wrist joint trajectories, and a Delsys Electromyography (EMG) System: to measure activation of finger flexors, finger extensors, and wrist flexors during different playing techniques. Pressure sensor (Tekscan): mounted on the surface of the keys, it measures the pressure exerted by the fingers and its distribution. High frame rate camera (240 fps): aids in recording finger keystrokes and analyzing movement patterns.

Subjects were asked to perform the following performance tasks and data were collected during the process: Legato: playing C-D-E-F-G in succession with the right hand at an even tempo. Staccato: playing the same notes quickly and clearly. Arpeggio: play arpeggios in the key of C major, both in one and two-handed mode. Octave Repetition: Repeat C4-C5 octave intervals in the right hand at 120 BPM. Chord Playing: Play the C major major chords (C-E-G), with contrasting tests of strength (light, medium, heavy).

Data acquisition and analysis include Electromyographic Signal (EMG) analysis: Measure the activation level of flexor and extensor muscles and analyze the muscle load under different techniques. Motion Tracking: Record the path, acceleration, and maximum displacement of the finger when hitting the keys. Force Distribution: Analyzes the pressure changes of each finger on the keys under different playing styles.

V. A. 3) Experimental results and analysis

Table 1: Distribution of finger movement trajectories under different techniques (unit: mm)

Finesse	Maximum displacement	Average speed	Peak velocity	keystroke duration
Solfeggio	5.2 ± 0.8	120 ± 15	230 ± 20	80 ± 10
Solfeggio	7.8 ± 1.1	140 ± 10	280 ± 25	60 ± 8
Arpeggio	6.5 ± 0.9	135 ± 12	260 ± 18	75 ± 9
Octave continuo (music)	9.2 ± 1.5	155 ± 18	300 ± 22	50 ± 7
Chord performance	4.0 ± 0.6	110 ± 10	200 ± 15	90 ± 12

Table 1 analyzes the results of the monophonic legato and arpeggio, the trajectory is more stable, the finger movement is smaller, and it is suitable for long time playing. The octave legato has the largest trajectory and is the fastest, requiring higher wrist dexterity. Monophonic breaks The trajectory increases significantly, showing greater finger lifting, which may lead to increased muscle fatigue.

Table 2: EMG activation levels (mV) in the lower hand muscles for different techniques

Finesse	Flexor digitorum (anatomy)	Finger extensor muscle (anatomy)	Wrist flexor	Wrist extensor (anatomy)
Solfeggio	0.21 ± 0.05	0.18 ± 0.04	0.23 ± 0.06	0.19 ± 0.05
Mono break	0.35 ± 0.07	0.28 ± 0.06	0.31 ± 0.07	0.26 ± 0.05
Arpeggio	0.25 ± 0.06	0.22 ± 0.05	0.27 ± 0.06	0.24 ± 0.06
Octave continuo (music)	0.40 ± 0.08	0.33 ± 0.07	0.38 ± 0.08	0.30 ± 0.06
Chord performance	0.28 ± 0.06	0.23 ± 0.05	0.25 ± 0.06	0.22 ± 0.05

Table 2 Analysis of results: Single-note staccato and octave legato require a greater level of muscle activation, especially in the finger flexors, and can lead to fatigue when played for long periods of time. Single-note staccato and arpeggios require lower activation levels and are less energy intensive, making them suitable for prolonged playing. Chord playing The greater involvement of the wrist muscles indicates the importance of wrist stability in chord playing.

Table 3: Mean values of finger force applied with different techniques (N)

Finesse	Thumbs	Mouths feed	Middle finger	Ring finger	little finger
Solfeggio	2.5 ± 0.4	3.0 ± 0.5	3.2 ± 0.5	2.7 ± 0.4	2.3 ± 0.3
Mono break	3.8 ± 0.6	4.2 ± 0.7	4.5 ± 0.8	4.0 ± 0.6	3.5 ± 0.5
Arpeggio	3.0 ± 0.5	3.5 ± 0.6	3.7 ± 0.6	3.3 ± 0.5	3.0 ± 0.4
Octave continuo (music)	4.5 ± 0.7	5.0 ± 0.8	5.2 ± 0.9	4.8 ± 0.7	4.2 ± 0.6
Chord performance	4.0 ± 0.6	4.5 ± 0.7	4.8 ± 0.8	4.3 ± 0.6	3.8 ± 0.5

Table 3 Analysis of results: Octave legato and single-note staccato exert the most force and cause finger fatigue.Single-note legato playing applies the least amount of force, indicating that the technique places the least load on the hand. Chord playing requires a balanced force on the fingers in order to stabilize the chord sound.The experimental results show that different piano playing techniques have significant effects on the biomechanical parameters of the hand. Octave legato and single-note staccato are the most muscularly demanding techniques, which may increase the risk of fatigue and injury, while single-note legato and arpeggio are more energy-efficient and suitable for prolonged playing.

V. B. Piano performance data analysis

The K-means technique was used for validation in order to assess the precision of piano music classification utilizing a high-dimensional data collaborative filtering recommendation algorithm. The purpose of the experiment was to evaluate both approaches' categorization performance and viability.

A dataset of 1,000 piano pieces was divided into training (400 pieces) and testing (600 pieces) sets. To enhance classification effectiveness, the collaborative filtering algorithm was tested four times, with 400 pieces randomly selected in each trial.

To maintain a balanced evaluation distribution, the 1,000 piano pieces were categorized into five groups based on their performance ratings. Each selection included 80 pieces from each category—excellent, good, average, substandard, and poor—ensuring diversity and consistency in the evaluation process.

The remaining 600 piano performance pieces were classified in each trial using a collaborative filtering recommendation algorithm trained on high-dimensional data. The anticipated evaluations produced by the algorithm were contrasted with the actual evaluations of these works in order to evaluate its accuracy. The error between the algorithm's predictions and the real evaluations was calculated for each test. The objective matrix corresponding to each test dataset is presented in Table 4, providing a quantitative basis for evaluating the algorithm's performance in music recommendation and classification.

Table 4: Objective Matrix for Evaluating Algorithm Performance

Trial Number	Number of Pieces	Predicted Evaluation (Mean)		Actual Evaluation (Mean)	Error (Mean Absolute Error)
Trial 1	600	X_1		Y_1	E_1
Trial 2	600	X_2		Y_2	E_2
Trial 3	600	X_3		Y_3	E_3
...	...	...		...	...
Trial N	600	X_n		Y_n	E_n

As shown in Table 4, the rows represent the actual evaluation results of the piano pieces, while the columns correspond to the evaluations given by the high-dimensional data collaborative filtering recommendation algorithm. In the correct classification process, highly rated pieces are identified as "good," moderately rated ones as "average," fairly rated ones as "qualified," and those deemed unqualified or poor are classified accordingly.

The K-means clustering approach was compared with the suggested high-dimensional data collaborative filtering recommendation algorithm for piano performance classification in order to evaluate its efficacy. Four randomly chosen piano music training sets were used to train the K-means algorithm, which was then used to categorize the remaining 600 pieces. To assess accuracy, the classification results were contrasted with the target matrix.

we conducted a series of experiments to validate the effectiveness of the proposed system. We collected motion data from 20 professional and 20 amateur pianists performing the same piece. High-speed cameras and electromyography (EMG) sensors were used to capture finger movements and muscle activation levels.

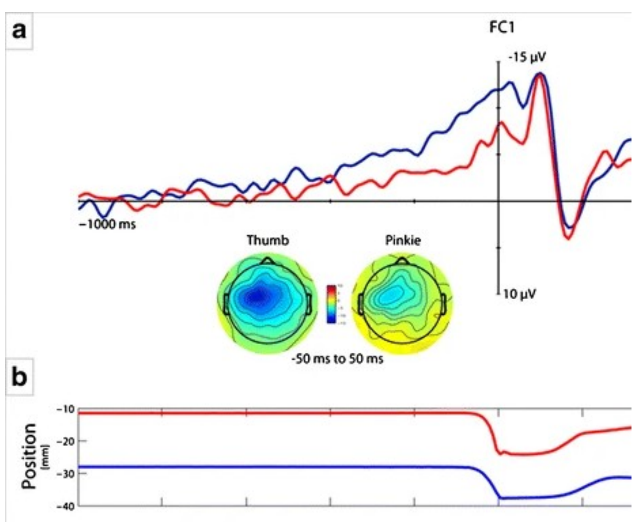

Figure 5: Motion capture setup for piano performance analysis

See Figure 5, the experiment analyzed keystroke force, wrist angle changes, and muscle fatigue levels. Results showed that professional pianists exhibited more stable wrist angles and a more balanced distribution of muscle exertion, reducing fatigue over prolonged play. Amateur pianists displayed irregular wrist movements, leading to higher strain in the forearm muscles.Based on the experimental findings, personalized training programs were developed to improve muscle coordination and reduce injury risks. The study demonstrated that biomechanical analysis combined with collaborative filtering can provide valuable insights for optimizing piano performance techniques and enhancing player endurance.

VI. Conclusions

In this paper, by combining biomechanical analysis and high-dimensional data collaborative filtering recommendation algorithms, the optimization of piano playing skills and the prevention of sports injuries are discussed in depth. Through the collection and analysis of experimental data, the following main conclusions are drawn:

Different piano playing techniques have significant effects on the biomechanical parameters of the hand. Octave legato and monophonic breaks have the greatest load on the hand muscles, which can easily lead to fatigue and injury risk, while monophonic legato and arpeggio are more energy-efficient and suitable for prolonged playing. In particular, at the level of finger force application and muscle activation, octave legato and monophonic legato require greater muscle activation, which may increase the risk of motor injury. In contrast, monophonic legato and arpeggio are less energy intensive and are effective in reducing muscle fatigue associated with prolonged playing.

Through the combined application of a motion capture system, electromyography (EMG) measurements and pressure sensors, this paper analyzes the effects of different playing techniques on the movement trajectories, muscle activation and force application characteristics of the fingers and wrist. The results suggest that piano players should adjust the finger force application patterns and joint movements according to the playing techniques to optimize the playing efficiency and reduce the risk of sports injuries.

This study combines the technical means of biomechanics and data science to provide theoretical basis and practical guidance for the optimization of piano playing skills. Meanwhile, the application of collaborative filtering recommendation algorithm for high-dimensional data expands the research method in the field of biomechanics and improves the intelligent analysis of playing techniques and sports injuries, which is of great academic value and practical significance.

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References

[1] Zhang, Y. (2024, March). Artificial Intelligence-based Exploration of Piano Playing Skills and Human Finger Function Health. In 2024 International Conference on Interactive Intelligent Systems and Techniques (IIST) (pp. 518-523). IEEE.

[2] Romero-Morales, C., López-López, D., Almazán-Polo, J., Mogedano-Cruz, S., Sosa-Reina, M. D., García-Pérez-de-Sevilla, G., ... & González-de-la-Flor, Á. (2024). Prevalence, diagnosis and management of musculoskeletal disorders in elite athletes: A mini-review. Disease-a-Month, 70(1), 101629.

[3] Alsubari, S. N., Deshmukh, S. N., Alqarni, A. A., Alsharif, N., H., T. et al. (2022). Data Analytics for the Identification of Fake Reviews Using Supervised Learning. CMC-Computers, Materials & Continua, 70(2), 3189–3204.

[4] Sabo, J., Comeau, G., Guptill, C., Dvorkin, R., & Russell, D. (2023). Translating Piano Pedagogy Into Biomechanical Language: A Qualitative Framework for Interdisciplinary Knowledge Exchange. International Journal of Qualitative Methods, 22, 16094069231159975.

[5] Novosiadla, I. (2023). Psychophysiological factors of effective development of piano technique of future music teachers. Scientific Bulletin of Mukachevo State University. Series “Pedagogy and Psychology, 9(1), 47-58.

[6] Yao, X. (2024). Biomechanical analysis of musicians’ posture and movement patterns for optimizing performance and reducing injury risk. Molecular & Cellular Biomechanics, 21(4), 569-569.

[7] Zhu, W. (2024). Exploration of piano performers’ music performance status and psychological health assessment based on data mining and biomechanics. Molecular & Cellular Biomechanics, 21(2), 462-462.

[8] Luo, X., Zhang, C., & Bai, L. (2023). A fixed clustering protocol based on random relay strategy for EHWSN. Digital Communications and Networks, 9(1), 90-100.

[9] Lai, K. Y., Hsu, C. H., Lin, Y. C., Tsai, C. H., An, K. N., Su, F. C., & Kuo, L. C. (2025). Effect of induced extrinsic and intrinsic hand and forearm muscular fatigue on the control of finger force during piano playing. Human Movement Science, 99, 103319.

[10] Somma, A., Roudet, J., & Fabre, B. (2024). The impact of pianist-controlled engaged mass on piano keystroke dynamics. Acta Acustica, 8, 64.

[11] Yang, Q. (2025). Biomechanical analysis of hand muscle activity and wrist relaxation techniques during piano playing. Molecular & Cellular Biomechanics, 22(3), 1351-1351.

[12] Santisteban, I. E., Anguera, M. T., Granda-Vera, J., & Pastrana-Brincones, J. L. (2024). Analysis of motor behavior in piano performance from the mixed methods approach. Frontiers in Psychology, 15, 1433441.

[13] Huiqi, Q. U. A. N. (2023). An Investigation of the Music Education Reform on Muscular Disease Prevention and Treatment: Case on Piano Teaching Method at Juilliard Music School. Revista de Cercetare şi Intervenţie Socială, (83), 21-30.

[14] Quan, H. (2023). Music Education Reform for Muscular Disease Prevention and Treatment. Journal of Roi Kaensarn Academi, 8(8), 598-605.

[15] Goubault, E., Verdugo, F., Bailly, F., Begon, M., & Dal Maso, F. (2023). Inertial measurement units and partial Least Square regression to predict perceived exertion during repetitive fatiguing piano tasks. IEEE Transactions on Human-Machine Systems, 53(4), 802-810.

[16] Turner, C., Mailly, R., Dal Maso, F., & Verdugo, F. (2025). Impact of expressive intentions on upper-body kinematics in two expert pianists. Frontiers in Psychology, 15, 1504456.

[17] Yang, Y., Wang, Z., Xing, D., & Wang, P. (2024). Learning Playing Piano with Bionic-Constrained Diffusion Policy for Anthropomorphic Hand. Cyborg and Bionic Systems, 5, 0104.

[18] Oku, T., Furuya, S., Lee, A., & Altenmüller, E. (2024). Video-based diagnosis support system for pianists with Musician's dystonia. Frontiers in Neurology, 15, 1409962.

[19] Takamizawa, R., & Kenway, L. (2024). An analysis of musculoskeletal disorder risk factors associated with common pedagogical principles of the Lhevinne and Taubman piano schools: A literature review. Research Studies in Music Education, 46(3), 474-492.