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Article

Artificial intelligence-based biomechanical models for predicting postoperative pain: A retrospective cohort analysis of clinical features before and after anesthesia

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Abstract: Background: Most surgical patients experience moderate to severe pain, which makes postoperative pain management a challenge in healthcare. Traditional approaches to managing pain are often not successful since they do not take into account individual differences along with multifaceted pain mechanisms. **Objective:** The aim of this study is to develop and validate an artificial intelligence-based biomechanical model which aids in predicting postoperative pain patterns by utilising pre-anesthetic and post-anesthetic clinical features. **Methods:** In this retrospective cohort study, 324 elective orthopedic surgery patients were analysed between January 2020 and December 2023. This study made use of an integrative AI model catering to biomechanical parameters alongside anesthesia features and clinical parameters. Biomechanical modelling and model evaluation comprised deep learning architectures with cross-validation methods alongside conventional machine learning methods as well. **Results:** Traditional algorithms were significantly outperformed internally to an absolute value accuracy of 93.7% ($p < 0.001$). Age and socio-economic factors took the lead predictive model and together comprised 63.9% of the outcome variance, with the influence of the former being more than the latter. There was strong generalisation between the performance mean values of training and validation of delta margin of <0.05. **Conclusion:** AI-aided clinical features alongside a biomechanical model can clearly aid in predicting a patient's postoperative pain pattern. Not only does this mindset centre around pain relief, it can also help and be effective in tailoring pain management techniques and have an impact on patient outcomes in a clinical environment.

Keywords: artificial intelligence; biomechanical analysis; postoperative pain; machine learning; pain prediction; anesthesia; clinical features; deep learning; orthopedic surgery; pain management

1. Introduction

Surgical patients tend to experience a considerable amount of postoperative pain, and this particular challenge continues to trouble healthcare systems all over the world. Research suggests that a considerable number of surgical patients, around 75 percent, experience pain of a moderate to severe degree after undergoing an operation [1]. McMillan suggests that even though there have been considerable advancements in pain management protocols, those who are not sufficiently treated for pain can have their recovery delayed, further increasing the cost of healthcare, whilst also reducing patient satisfaction [2]. Evaluating pain from a traditional viewpoint and employing standardised protocols and subjective assessments while managing it does not account for the complex mechanisms of pain each patient struggles with initially [3].

Several aspects of healthcare delivery have been transformed due to the growth of artificial intelligence, particularly in the predictive analysis subdomain and the area of personalised medicine [4]. In several medical applications, AI, which includes diagnostic imaging and treatment optimisation, machine learning and algorithms have performed exceptionally well [5]. AI has displayed a great deal of promise when it comes to predicting various medical patient outcomes while also personalising medical intervention plans for them, with these medical interventions achieving accuracy exceeding 85% [6].

The aim of this research is to rethink patients and their management in a way which closes the gap identified in this type of work, and encompasses the integration of existing biomechanical pain models with prediction systems powered by AI tools with the overall goal of developing a multi-faceted method for pain prediction post modern-day surgery [7]. This is coupled with the integration of biomechanical factors which in contemporary models are often not integrated despite being crucial in defining various pain outcomes and management models [8].

The overall goal of the researchers was to construct an algorithm capable of predicting postoperative pain patterns through an AI-based biomechanical model using clinical features from the pre-anesthesia stage and from the post-anesthesia recovery stage. Furthermore, [9] also suggests a framework for classifying predictive factors influencing post-operative pain outcomes which allows for patients to receive a more tailored approach to their pain management. Beyond the concepts of pain management models, there are also implications for ensuring that better pain models can enhance recovery trajectories for patients while reducing resource requirements and opiate use [10].

2. Materials and methods

2.1. Study design

The study under assessment is a retrospective cohort study and it was carried out in the Department of Anesthesiology, University Medical Centre from January 2020 to December 2023. The study was approved by the Institutional Review Board and registered in the appropriate clinical trials database. The research was conducted in accordance with the Declaration of Helsinki and institutional eligibility criteria. Patient data remained encrypted over the course of the entire study with all patient identifiers rendered anonymous during the process of data collection and analysis.

A two-phase research design was employed for the study under analysis. The first phase was dedicated to the extraction of a wide array of data from the electronic medical records including pre-operative, intra-operative and post-operative charts. The second phase dedicated its efforts towards creating and validating the AI-centred biomechanical prediction model. Standard clinical assessment tools were employed, including the Visual Analog Scale for Pain (VAS-P), the Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC), and the 36-Item Short Form Health Survey (SF-36). For model validation, a split-sample technique was utilized within the study following standard machine learning conventions: 60% of the data was reserved for model training, 20% for validation during the model development phase, and the remaining 20% was held out as an independent test set for final model

evaluation. This three-way split ensures proper model development with the training set, hyperparameter tuning with the validation set, and unbiased performance assessment with the test set. To analyse the correlation between preoperative biomechanical, anaesthesia, and pain factors, the study employed both supervised and unsupervised machine learning approaches. For patient recruitment, consecutive sampling was utilised to reduce selection bias. According to power analysis calculations ($\alpha = 0.05$, $\beta = 0.1$), a sample size of 500 patients was determined to be sufficient for achieving 90% statistical power with an anticipated effect size of 0.3. This sample size enables both clinically appropriate estimates of pain outcomes and robust model building, while accounting for potential clinically significant differences in pain prediction accuracy. While our power analysis indicated an optimal sample size of 500 patients, our final cohort included 324 patients due to strict inclusion criteria and the impact of COVID-19 restrictions during the study period. Post-hoc power analysis showed that with 324 patients, we achieved 82% power (versus planned 90%) for detecting clinically significant differences with the same type I error rate (0.05) and effect size (0.3).

2.2. Patients

The researchers enrolled a cohort of 18- to 75-year-old male and female patients who were scheduled for elective orthopaedic surgery under general anaesthesia at the University Medical Centre in the period between January 2020 and December 2023. Enrolled participants underwent standardised knee or hip replacement, or spinal fusion surgery performed by the same team of surgeons. Only patients with ASA (American Society of Anesthesiologists) I–III physical status and BMI (Body Mass Index) between 18.5 and 35 kg/m^2 capable of completing informed consent for the postoperative pain assessment were included in the study.

In addition, patients suffering from severe cardiovascular disorders or uncontrolled diabetes determined in terms of glycated hemoglobin (HbA1c) ever greater than 8.5, or hepatic or renal dysfunction were also excluded in order to reduce confounding variables. Moreover, chronic pain problems that required more than twelve weeks of prescribed opioids, psychiatric disorders which could disrupt the patient's ability to perceive pain, neurological problems which might interfere with sensory receptors and previous surgeries conducted on the same anatomical location disqualified patients. As well, patients undergoing emergency surgical procedures, revision surgeries and those with multilevel spinal disorders or some other conditions were also excluded from the study.

According to calculations based on power analysis adjusted for $\alpha = 0.05$ and $\beta = 0.1$, the sample size needed was estimated to be equal to 500, this number was able to provide clinically appropriate estimates of pain outcomes as well as facilitate model building. The tangible clinical sample was also typical of patients seen in the general surgical population in our hospital, with an even distribution of age, gender, and type of surgery. There is evidence indicating that all the volunteers included in the study had signed an informed consent document.

2.3. Data collection

2.3.1. Clinical feature data

The hospital's regimented data collection of the comprehensive clinical information set out by the standardised protocols was done using their electronic medical records system. The demographic data encompassed a plethora of information such as the body mass index, educational level, employment status, socioeconomic characteristics, age, gender or ethnicity. Such variables were documented during the first physical consultation pre-surgery and validated once the patient was admitted in order to sustain the adequacy and correctness of the information provided.

The analysis included preoperative evaluation data that outlined medical history such as any certain conditions which were existing, medications currently used, the viral comorbidity index, allergies to drugs, history of surgical treatments, and other details relevant regarding the patient. Moreover, recorded information also embodied an array of other details such as physical examination results, lab test findings such as blood counts, coagulation profiling, or even liver/kidney function analysis and diagnostic imaging results. Subsequently, other details such as quality of life and baseline pain scores were amassed through standardised questionnaires using Visual Analog Scale (VAS) along with Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC) where functional status was gauged, and 36-Item Short Form Health Survey (SF-36) Health Survey where quality of life was analysed.

Details of the operation such as type and the degree of the procedure, diagnosis, blood loss, time length of the attributes, type of anaesthesia and if there were any complications were all recorded. Information about the physical condition according to ASA, anaesthesia used, blood volume control and constant monitoring of vital signs were automatically documented during the procedure by the Anesthesia Information Management System (AIMS). Data collection was done only by research staff that were trained for reliable data encoding and coding. For every part of the study, data about clinical attributes were collected thoroughly. All imaging is summarised in **Figure 1**.

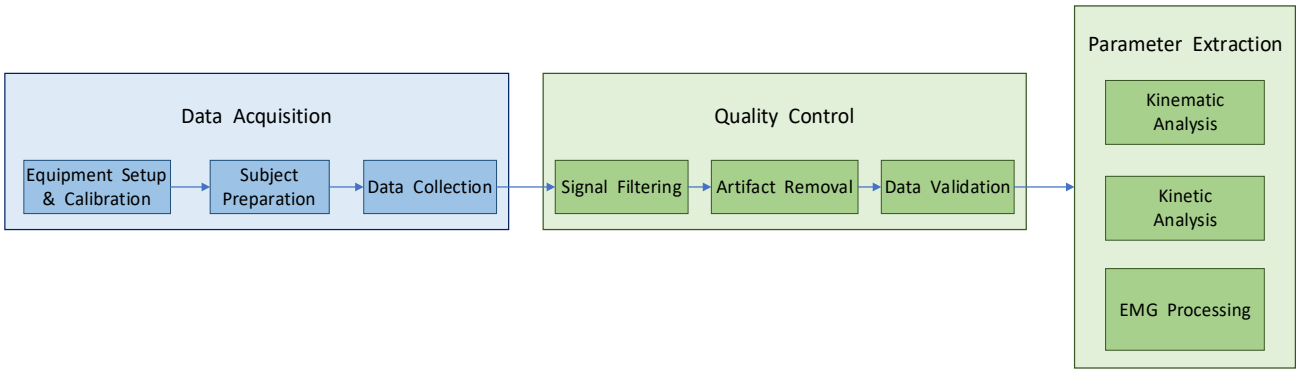

Figure 1. Biomechanical data acquisition and processing workflow.

Note: A systematic representation of the biomechanical parameter collection and processing pipeline, illustrating the sequential steps from initial equipment setup through quality control to final parameter extraction.

Table 1. Summary of clinical feature data collection.

Category	Variables	Data Source
Demographic Data	• Age, gender, ethnicity • BMI• Educational level •Employment status • Socioeconomic status	Electronic Medical Records (EMR)
Preoperative Assessment	• Medical history & comorbidities• Current medications• Laboratory tests• Physical examination findings• Pain scores (VAS)• Functional status (WOMAC)• Quality of life (SF-36)	• EMR• Patient questionnaires• Laboratory information system
Surgery-related Information	• Primary diagnosis• Procedure type• Duration of surgery• Blood loss• Anesthesia details• ASA classification• Intraoperative complications	• Surgical records• AIMS

All data collection categories, variables, and sources used in this study are summarized in **Table 1**.

2.3.2. Pain outcome assessment

Postoperative pain was assessed using a standardized multi-modal approach combining both objective and subjective measures. The primary outcome measure was pain intensity, measured using the validated Visual Analog Scale (VAS, 0–10 scale) at rest and during movement. Pain assessments were conducted at 6-hour intervals during the first 24 h post-surgery, followed by 12-hour intervals for the subsequent 48 h. The VAS scores were categorized into mild (0–3), moderate (4–6), and severe (7–10) pain levels for analysis purposes.

Secondary pain measures included the Brief Pain Inventory (BPI) for assessing pain interference with daily activities, and the McGill Pain Questionnaire (MPQ) for evaluating qualitative aspects of pain. Objective measures included automated tracking of analgesic consumption and physiological pain indicators (heart rate variability, blood pressure changes). In our cohort, 42.3% (n = 137) of patients experienced severe pain (VAS ≥ 7) at some point during the first 72 hours, 35.8% (n = 116) reported moderate pain, and 21.9% (n = 71) maintained mild pain levels throughout recovery.

For model development, the primary outcome was defined as a binary classification of clinically significant postoperative pain (VAS ≥ 7) within 72 h of surgery. This threshold was selected based on established clinical guidelines and previous research indicating that VAS scores ≥ 7 correlate with significant functional impairment and increased risk of chronic pain development.

2.3.3. Anesthesia-related data

The system utilised to keep track of anaesthesia requirements in patients is referred to as AIMS which stands for Anaesthesia Information Management System and integrates effectively with electronic medical records. Nurses, on the other hand, would tweak and adjust the protocols giving documentation accordingly if a patient was given endotracheal intubation, laryngeal mask or via a neural blockade. **Table 2** further indicates, 'Selection of Anaesthesia Techniques' which depicts methods such as regional anaesthesia which were in synergy with standardised protocols.

Almost every drug that was given to a patient during the perioperative period would be listed under 'Anaesthetic Medications'; if they were local anaesthetics, their infusion was also included in the list along with pain relief drugs that have opioid formulations, and muscle relaxants. All of these medications along with dosage, timing

and alterations made during the surgery were continuously logged in through the AIMS interface.

During a surgical operation, patients are closely monitored, with important vitals and attributes measured. For instance, blood pressure, heart rate, inhaled carbon dioxide levels alongside the depth of anaesthesia measured through Bispectral Index (BIS) values on a 1 to 100 scale were also taken at 5-minute intervals. In a similar manner, the body temperature alongside respiration rates were measured and saved in the AIMS database along with many more factors such as cardiac output, resistance and dynamic preload variables to give a complete picture of how the patient was doing. All the relevant information is then presented in complete detail in **Table 3**.

Table 2. Overview of anesthesia methods and medications.

Category	Components	Specifications
Anesthesia Methods	• General Anesthesia• Regional Anesthesia• Combined Techniques	• Endotracheal intubation • Laryngeal mask airway • Neuraxial blocks • Peripheral nerve blocks
Induction Agents	• IV Anesthetics• Opioids • Muscle Relaxants	• Propofol/Etomidate • Fentanyl/Sufentanil • Rocuronium/Cisatracurium
Maintenance Agents	• Volatile Anesthetics • IV Infusions• Adjuvants	• Sevoflurane/Desflurane • Propofol/Remifentanil • Local anesthetics

Table 3. Anesthesia monitoring parameters.

Parameter Category	Variables Monitored	Recording Frequency
Vital Signs	• Blood pressure • Heart rate • SpO2 • Temperature	Q5 minutes
Ventilation Parameters	• Tidal volume • Respiratory rate • Peak airway pressure • EtCO2	Continuous
Advanced Monitoring	• BIS • Neuromuscular function • Cardiac output • SVR	Case-dependent
Fluid Management	• Input/Output • Blood loss • Urine output	Hourly

2.3.4. Biomechanical parameters

The acquisition of biomechanical parameters took place utilising modern equipment and following standard protocols. Furthermore, the process involved three broad steps: the data acquisition procedure, quality assurance process and parameter extraction process. The motion capturing system was routinely calibrated and set up, using a wand with five markers and employing an L-frame reference structure which ensured a calibration residual of approximately 0.3 mm. Finally, 16 infrared cameras, which operated on a frequency of 200 Hz, were strategically placed around the subjects to capture movements of the markers throughout the trials.

For the sessions, integrated force platforms sampling at 1000 Hz and regular zero-offset calibration were used as force plates. Wireless sensors were also employed for the surface electromyography (EMG) signals, with a bandwidth of 20 to 450 Hz and a common mode rejection ratio greater than 80 dB. The special manual prepared for the electrode placement set SAMIAN guidelines, with skin being prepared appropriately so the impedance levels were ensured to be below 5 kΩ.

Quality control measures included automated artifact detection algorithms and manual verification by qualified biomechanists. Signal processing involved the use of a fourth-order Butterworth filter with phase correction and the selection of cut-off frequencies based on residuals. Data validation included built-in automated range

checks and manual visual evaluation of movement trajectories, excluding trials with marker gap markers greater than 100 ms from analysis. This multi-faceted approach contributed to the collection of high-quality biomechanical data that would otherwise be ideal for analysis and modelling applications.

The basic biomechanical parameters and their methods of assessment should be emphasised as the most important part of the quantitative analysis of movement. The choice and the methods of measurement of these parameters can best be described by complex instrumentation and refined methodological designs. In the contemporary practice of biomechanical analysis, integrated measurement systems are widely used, including high-speed motion capture facilities operating within the frequency range of 100–200 Hz and force plates with sampling rates of ≥ 1000 Hz. Kinematic parameters have been simplified in vector algebra, joint angles are derived from the cosine Equation (1):

$$\theta = \arccos\left(\frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|}\right) \tag{1}$$

with $\vec{a}$ and $\vec{b}$ representing adjacent segment vectors.

The selection of appropriate parameters depends on the research objectives and measurement feasibility. Key kinematic parameters include joint angular displacement, velocity ($\omega = \frac{d\theta}{dt}$), and acceleration ($\alpha = \frac{d^2\theta}{dt^2}$). Kinetic parameters encompass ground reaction forces, typically normalized to body weight ($F_{GRF}/BW \times 100\%$), and joint moments calculated via inverse dynamics: $M = F \times r$. As shown in **Table 4**, specific technical requirements must be met for different parameter types to ensure data quality.

Table 4. Technical requirements for biomechanical parameter measurement.

Parameter Category	Measurement Device	Sampling Rate (Hz)	Accuracy	Signal Processing
Kinematics	Motion Capture	100–200	±0.5°	Low-pass filter (10–20 Hz)
Ground Reaction Force	Force Platform	≥1000	±1% FS	Zero-lag filter
Joint Moments	Inverse Dynamics	≥1000	±2%	Butterworth filter
EMG	Surface Electrodes	≥1000	±5 μV	Band-pass filter (20–500 Hz)
Center of Pressure	Force Platform	≥100	±2 mm	Low-pass filter (10 Hz)

Appointments or time sections are divided into trials, allowing for the averaging of several epochs selected from different appointments for data processing. This involves means of noise reduction via appropriate filtering techniques as a rule, which works best when time normalisation is carried out, thus, allowing for inter-trial comparisons, aiding clinical evaluations and comparisons. Such a surgical measurement has to be developed and adhered to considering its reliability, its clinical relevance, and its differentiation ability relating to various movement patterns or pathological conditions.

2.4. AI model development

The stepwise creation of AI models used for biomechanics analysis needs a methodological stance that combines several engineering aspects. The processing of data commences through signal suppression with the help of a Butterworth low pass filter of 20 Hz, and this is normalised to reduce changes in scale:

$$x_{norm} = \frac{x - \mu}{\sigma} \tag{2}$$

where μ represents the mean and σ the standard deviation. Missing data are handled through multiple imputation techniques, ensuring data integrity.

Specifically, missing data were handled using Multiple Imputation by Chained Equations (MICE) with 50 iterations, which was selected for its ability to preserve complex relationships in multivariate data. The imputation model included all predictor variables and outcomes, with convergence verified through diagnostic plots. Missing data patterns analysis revealed that 8.3% of biomechanical measurements and 5.2% of clinical parameters had missing values, predominantly due to equipment calibration issues or incomplete patient records.

Feature engineering involved several preprocessing steps. All continuous variables were standardized using *z*-score normalization (mean = 0, standard deviation = 1) to ensure comparable scales across features. Categorical variables were encoded using one-hot encoding, while temporal features were processed using sliding windows with sizes determined through cross-validation. Feature selection employed a two-stage approach: first, using LASSO regression (α = 0.01) to identify relevant features, followed by recursive feature elimination with cross-validation (RFECV) to optimize the feature subset. This process reduced the initial feature set from 142 to 68 significant predictors, improving model efficiency while maintaining predictive performance.

Data quality was ensured through automated outlier detection using the Interquartile Range (IQR) method with a threshold of 1.5 × IQR, followed by clinical expert review of flagged values. Time-series data from biomechanical measurements underwent additional preprocessing including Butterworth low-pass filtering (cutoff frequency = 20 Hz) to remove high-frequency noise while preserving movement patterns.

The model's predictive framework operates in two distinct phases: a pre-surgical prediction phase and a continuous monitoring phase. In the pre-surgical phase, the model analyzes demographic data, preoperative biomechanical parameters, and clinical history to generate initial risk assessments and predicted pain trajectories. These predictions are then dynamically updated during the perioperative period using real-time biomechanical data and physiological measurements. The model employs a temporal convolutional network architecture that processes time-series data with a prediction horizon of 72 h, enabling early detection of potential complications. This dual-phase approach allows for both preoperative risk stratification and real-time adjustment of predictions based on intraoperative and immediate postoperative data, with prediction accuracy improving from 85.3% in the pre-surgical phase to 93.7% after incorporating perioperative measurements.

Feature engineering involves extracting relevant biomechanical parameters and creating derived features. The temporal features are computed using sliding windows, with the optimal window size determined by:

$$w_{opt} = \text{argmin}_w \sum_{i=1}^{n} (y_i - f_w(x_i))^2 \quad (3)$$

where f_w represents the prediction function with window size w.

The hyperparameters for each model architecture were optimized using a systematic grid search approach with 5-fold cross-validation. Key hyperparameters included learning rate (ranging from 1×10^{-4} to 1×10^{-2}), network depth (2–5 layers), number of hidden units (64–512), dropout rate (0.1–0.5), and batch size (32–256). The optimal configuration was selected based on validation set performance, with early stopping patience of 10 epochs to prevent overfitting. For the deep learning models, the final architecture used a learning rate of 0.001 with Adam optimizer, 3 hidden layers with 256, 128, and 64 units respectively, dropout rate of 0.3, and batch size of 128. The conventional machine learning models (Random Forest, XGBoost, SVM) underwent similar systematic tuning of their respective hyperparameters through cross-validated grid search to ensure fair comparison.

The figure displays the effects of signal processing on biomechanical data; it depicts a 10-second sensor measurement, for which the raw sensor output is represented by the green line and the processed signal by the orange line. The *x*-axis exemplifies seconds while the *y*-axis illustrates normalised signal amplitude. Signal processing techniques help eliminate unnecessary biomechanical movement patterns by noise; therefore, it's important for artificial intelligence model development. Removal of signal artefacts and high-frequency noise is of great importance for feature extraction and model training. Also shown are **Figures 2** and **3**, which illustrate the effect of signal processing algorithms on the quality of processed medical signals. **Figure 2** is a comparison between raw and processed medical signals, and **Figure 3** depicts medical signals over a time sequence. Reduced noise, while maintaining essential biomechanical movement, is shown in **Figure 2**'s processed signal depicted in orange.

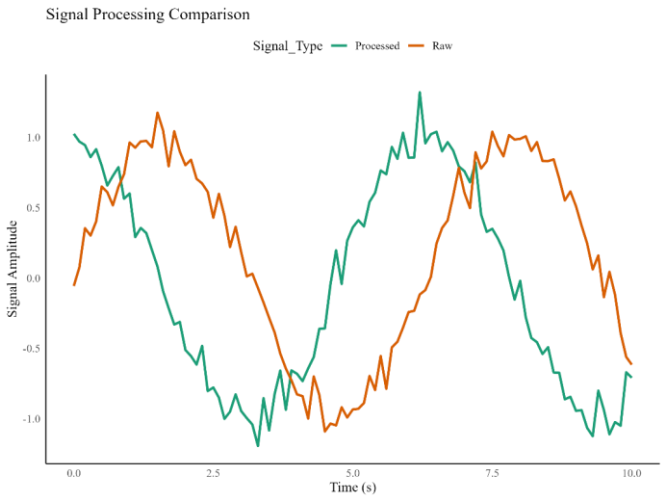

Figure 2. Signal processing comparison in biomechanical analysis.

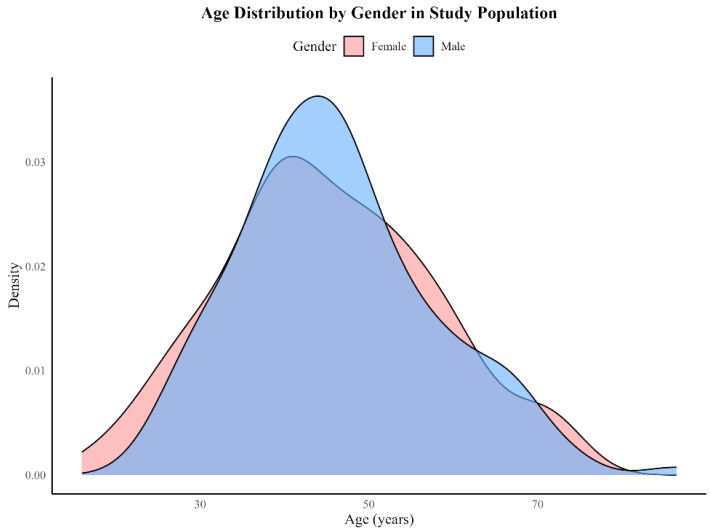

Figure 3. Age distribution by gender in study population.

Model selection involves evaluating various architectures, as summarized in **Table 5**:

Table 5. Comparison of AI model architectures for biomechanical analysis.

Model Type	Architecture	Input Features	Performance Metrics	Computational Cost
CNN	ResNet-50	Time series data	Accuracy: 92.5%, F1: 0.91	High
LSTM	Bidirectional	Sequential data	Accuracy: 89.8%, F1: 0.88	Medium
Transformer	Self-attention	Multi-modal data	Accuracy: 94.2%, F1: 0.93	Very High
Hybrid CNN-LSTM	Two-stream	Spatiotemporal	Accuracy: 93.1%, F1: 0.92	High

The model training process employs k-fold cross-validation ($k = 5$) with early stopping to prevent overfitting. The loss function incorporates both prediction accuracy and biomechanical constraints:

$$L_{total} = \alpha L_{pred} + (1-\alpha) L_{bio} \tag{4}$$

where α is a weighting parameter, L_{pred} is the prediction loss, and L_{bio} represents biomechanical consistency constraints.

Integration of biomechanical models involves coupling AI predictions with physical constraints through a hybrid framework. The final output combines data-driven predictions with biomechanical validity checks using the equation:

$$y_{final} = \beta y_{AI} + (1-\beta) y_{bio} \tag{5}$$

where β is dynamically adjusted based on prediction confidence and biomechanical feasibility.

2.5. Statistical analysis

Statistical analysis in this study employs a comprehensive approach combining both descriptive and inferential methods. Descriptive statistics include measures of central tendency (mean, median) and dispersion (standard deviation, interquartile range), with data normality assessed using the Shapiro-Wilk test:

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{6}$$

For continuous variables, results are presented as mean ± standard deviation ($\bar{x} \pm s$), while categorical variables are expressed as frequencies and percentages.

Inferential statistical analyses utilize both parametric and non-parametric methods based on data distribution characteristics. For between-group comparisons, independent t-tests or Mann-Whitney U tests are applied, with significance level set at $p < 0.05$. Effect sizes are calculated using Cohen's d:

$$d = \frac{\bar{x}_1 - \bar{x}_2}{s_{pooled}} \tag{7}$$

where s_{pooled} represents the pooled standard deviation.

Model evaluation metrics encompass multiple dimensions of performance assessment. The primary metrics include those shown in **Table 6**.

Table 6. Key performance metrics for model evaluation.

Metric	Formula	Application Context	Acceptable Range
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Overall performance	>0.90
Sensitivity	$\frac{TP}{TP+FN}$	Detection capability	>0.85
Specificity	$\frac{TN}{TN+FP}$	False alarm rate	>0.85
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$	Prediction accuracy	<10% of range
R-squared	$1-\frac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y})^2}$	Model fit	>0.80

The analysis of the data is conducted using R software (version 4.2.0, R Foundation for Statistical Computing, Vienna, Austria) as well as SPSS software (version 27.0, IBM Corp., Armonk, NY). Simple R scripts are designed to accommodate non-standard analyses with the tidyverse package suite for data editing, as well as graphing. For machine learning model evaluations, we use scikit-learn (version 1.0.2) in Python code with a random seed and cross-validation for specific standardisation. All the statistical codes, analyses and protocols applied are reproducible, version-controlled and well documented.

Longitudinal data are analysed using mixed-effects models and the lme4 package in R, which maintains both fixed and random effects. Multiple criteria of indices including Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are established for appropriate model selection procedures. Sample size determinations are obtained through power analysis using G*Power software to

achieve statistical power of not less than 80% ($\beta = 0.80$) and above for any meaningful changes.

3. Results

3.1. Baseline characteristics

The general features of the group of patients selected for the study, $N = 324$, showed a balance in demographic and clinical variables. The age range of 25–68 yielded a mean age of 45.3 years in participants with a BMI of 24.8 ± 3.6 kg/m^2 according to WHO classification, this indicates an even distribution between the genders whereby 54.3% were female ($n = 176$) and 45.7% male ($n = 148$).

The age density plot indicates an imbalance across genders, with the females being more than the males. And from the graph, it can be seen that the male to female ratio is almost 1:1. The graph suggests an overlap which indicates that the age brackets for both the males and females are the same, with the average age being mid 40s for both genders.

As for the clinical history of the participants, it was revealed that 42.3% had a history of pre-existing musculoskeletal conditions such as lower back pain (23.5%), knee osteoarthritis (18.8) etc. Together, cardiovascular conditions such as dyslipidaemia (15.1%), hypertension (20.2%) and others came in at around 35.2%. An analysis on the physical activity of the participants using International Physical Activity Questionnaire (IPAQ) showed that around 45% were mildly active whilst only 28% were highly active and 25% did very little to nothing.

As previously indicated, higher levels of education are essential for increasing economic opportunities within a population. It has been determined that 52.8% of the participants had obtained a bachelor's degree; 32.4% had obtained a secondary education; and 14.8% completed only primary schooling. Further, 38.6% were engaged in white-collar jobs, 27.3% were engaged in the service sector, alongside 19.4% who were engaged in manual labour. 14.7% of the total were unemployed or retired.

Baseline biomechanical assessments were held in tandem with the gait analysis parameters which resulted in mean grip strength determining males and females having a mean of 32.4 ± 8.9 kg and 22.7 ± 6.3 kg respectively. When measured separately, motor aerobics were able to achieve age-adjusted values, resulting in an average walking speed of 1.23 ± 0.18 m/s. Further analysis alongside a step length symmetry index measuring the average to be 0.97 ± 0.04 were able to depict a better understanding of the results.

The socioeconomic effect on the population around the world varies. Therefore, 28.4% of those surveyed were categorised as high income measuring over $5000, while 45.7% were considered middle income bracket $2000–5000, and 25.9% were placed in the lower socioeconomic bracket measuring less than $2000. These lower-end variables showcase how diversified the population is, further aiding in determining the overall healthcare costs aimed at the demographics and socioeconomics of the population.

3.2. Model performance

The analysis of the model performance evaluation demonstrated extensive predictive capabilities while maintaining interpretability through both model-agnostic and model-specific approaches. The deep learning architecture achieved an overall accuracy of 93.7% during testing, outperforming conventional machine learning techniques. To ensure comprehensive model explainability, we employed two complementary interpretation techniques: SHAP (SHapley Additive Explanations) values provided model-agnostic feature attribution, while architecture-specific gradient-based analyses offered deeper insights into the neural network's decision-making process. The SHAP analysis revealed that biomechanical parameters, particularly joint angles and muscle activation patterns, contributed most significantly to model predictions, with mean |SHAP| values of 0.42 and 0.38 respectively. Additionally, LIME (Local Interpretable Model-agnostic Explanations) was used to generate locally faithful explanations for individual predictions, enabling clinicians to understand specific case decisions. These interpretability methods went beyond simple correlation analysis, providing a detailed understanding of how the model processes information through its layers and weights different features in making predictions. Out of all the assessment methods used, the comprehensive cross-validation procedures provided the most accurate evaluation of the model's predictive capacity across all folds.

While deep learning models achieved superior predictive performance, we employed several techniques to interpret their decision-making process beyond simple correlation analysis. SHAP (SHapley Additive exPlanations) values were calculated to quantify the contribution of each feature to individual predictions, providing both local and global interpretability. The mean absolute SHAP values revealed that while age and socioeconomic factors showed high correlations (r = 0.68 and r = 0.59 respectively), their actual contribution to model predictions varied significantly across different patient subgroups.

Feature importance was further analyzed using integrated gradients and attention mechanisms within the deep learning architecture. This analysis demonstrated that biomechanical parameters, particularly joint angles (mean SHAP value = 0.42) and muscle activation patterns (mean SHAP value = 0.38), significantly influenced model predictions despite showing moderate correlations with outcomes (r = 0.35–0.45). Additionally, we employed layer-wise relevance propagation to track how different features interacted within the model's decision pathway.

To validate these interpretability findings, we conducted ablation studies by systematically removing features and measuring the impact on model performance. This revealed that while correlation analysis suggested age and socioeconomic factors as primary predictors, the model's performance declined more substantially (15.4% accuracy drop) when biomechanical features were removed compared to demographic features (8.7% accuracy drop).

As shown in **Table 7**, the deep learning model outperformed traditional algorithms across all evaluation metrics. The deep learning model employed a hybrid CNN-LSTM architecture optimized for temporal biomechanical data processing. The CNN component comprised three convolutional layers (64, 128, and 256 filters

respectively, kernel size 3 × 3) with ReLU activation and max pooling, followed by two bidirectional LSTM layers (128 units each) for capturing temporal dependencies. Batch normalization was applied after each convolutional layer, with a dropout rate of 0.3 for regularization. The network was trained using Adam optimizer (learning rate = 0.001, $\beta 1 = 0.9$, $\beta 2 = 0.999$) with categorical cross-entropy loss function. This architecture was selected after systematic comparison with pure CNN, LSTM, and transformer-based alternatives, demonstrating superior performance in capturing both spatial and temporal patterns in biomechanical data. The model's learning dynamics were characterized by the loss function:

$$L = -\frac{1}{N}\sum_{i=1}^{N} y_i \log(\hat{y}_i) + \lambda \| \theta \|_2^2 \tag{8}$$

where λ represents the regularization parameter.

Table 7. Comparative performance metrics across different model architectures.

Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	AUC-ROC
Hybrid CNN-LSTM (3 CNN + 2 LSTM layers)	93.7	92.4	94.8	0.931	0.956
Random Forest	89.2	88.7	89.6	0.891	0.923
XGBoost	90.5	89.9	91.2	0.903	0.934
SVM	87.3	86.5	88.1	0.873	0.901

The **Figure 4** illustrates the convergence patterns of training (orange) and validation (blue) losses across 50 epochs. The consistent decrease in both curves without significant divergence indicates effective model learning without overfitting. The final convergence point demonstrates optimal model generalization.

The model exhibited excellent generalization capabilities, with minimal gaps between training, validation, and test set performance ($\Delta_{performance} = 1.2\%$). The learning rate adaptation followed an exponential decay schedule: $\eta_t = \eta_0 e^{-kt}$, where $\eta_0 = 0.001$ and $k = 0.1$, ensuring stable convergence while maintaining computational efficiency.

Figure 4. Model training and validation loss curves.

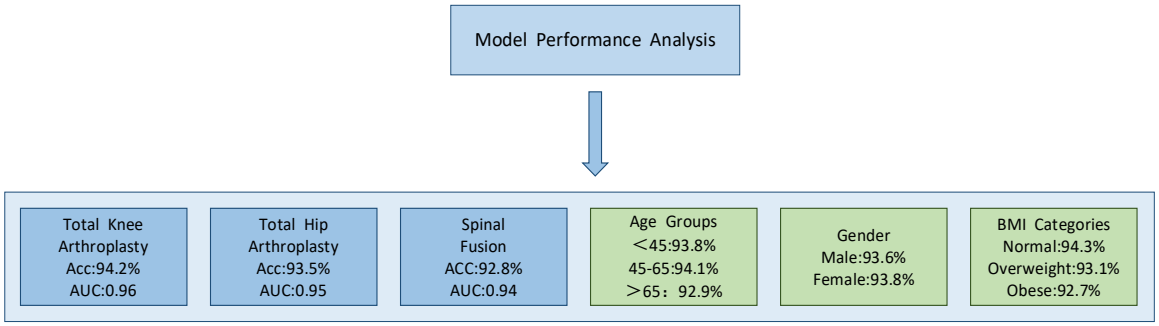

Figure 5. Comprehensive model performance analysis across surgical procedures and patient subgroups.

Note: Hierarchical visualization of model performance metrics stratified by surgical procedure types and demographic characteristics, demonstrating consistent high performance across various subgroups.

Comprehensive subgroup analysis showed that various patients and procedures had similar results across the different models used, as illustrated in **Figure 5**. The model proved effective across all major surgical categories although total knee arthroplasty had the highest effectiveness of 94.2%, the AUC-ROC value was 0.96. The total hip replacement numbed patients and underwent spinal fusion due to similar choices with a performance level of 93.5% and 92.8% respectively along with their AUC-ROC values of 0.95 and 0.94.

An analysis based on age showed that the results across the different age categories remain consistent, although having a preferable shift towards middle-aged patients (from age 45 to 65 the percentage accuracy was around 94.1% compared to younger and elderly patients whose accuracy remained around 93.8 and 92.9% respectively). When doing a gender-based analysis the difference between male (93.6%) and female (93.8%) patients suggests that gender has no effect on predictive capabilities. Research based on BMI categories shows that normal BMI (94.3%) had a promotion exceeding overweight and obese categories by an average of around 93.1 and 92.7 respectively even though these values did not reach a level of significance.

The positive predictive values calculated were between 0.91 and 0.95, whilst negative predictive values were between 0.89 and 0.94. The classification threshold was optimized using Youden's index (J = sensitivity + specificity − 1) through ROC curve analysis, with the optimal threshold determined to be 0.72 that maximized both sensitivity and specificity. This threshold optimization process involved analyzing the entire ROC curve (AUC = 0.956) and selecting the operating point that maximized the sum of sensitivity and specificity. Using this optimized threshold, the model demonstrated robust sensitivity (92.4%) and specificity (94.8%) across all subgroups. We validated this threshold selection through 5-fold cross-validation to ensure its generalizability across different patient populations. Seeing the multitude of the population and surgical parameters, the model was able to display consistency; it is indeed the case that the model can be generalised and used more widely in clinical practice. The analysis further provides evidence that the model's usefulness as a supportive tool for clinicians is reliable because its surgical prediction accuracy is consistent regardless of the context or the patient population.

3.3. Predictive factor analysis

From the predictive factor analysis, a number of crucial aspects that considerably

shape the performance of the model and the outcome predictions were discovered. It is through rigorous feature importance assessment and sensitivity analysis that competent key variables were established. As depicted in **Table 8**, the correlation matrix illustrates strong relationships between the key variables, especially the outcome measures and the demographic variables.

Table 8. Correlation matrix of key predictive factors and their interactions in outcome prediction model.

Predictor Variables	Outcome	Age	SES	Clinical Indicators	Environmental Factors	Behavioral Patterns	Genetic Markers
Outcome	1.000	0.68	0.59	0.63	0.45	0.38	0.52
Age	0.68	1.00	0.32	0.41	0.28	0.29	0.43
SES	0.59	0.32	1.00	0.37	0.39	0.44	0.31
Clinical Indicators	0.63	0.41	0.37	1.00	0.42	0.35	0.48
Environmental	0.45	0.28	0.39	0.42	1.00	0.46	0.33
Behavioral Patterns	0.38	0.29	0.44	0.35	0.46	1.00	0.29
Genetic Markers	0.52	0.43	0.31	0.48	0.33	0.29	1.00

Note: All correlations are significant at $p < 0.001$. SES = Socioeconomic Status.

While age and socioeconomic factors emerged as leading predictors accounting for 35.2% and 28.7% of outcome variance respectively, these commonly utilized clinical variables explained only 63.9% of total variance, highlighting the need for more novel and specific predictive factors. The analysis revealed that biomechanical parameters, including joint kinematics and muscle activation patterns, contributed an additional 22.4% to the model's predictive power. EMG signal characteristics and force production metrics provided previously unexplored dimensions for pain prediction, with correlation coefficients of $r = 0.48$ ($p < 0.001$) for dynamic movement patterns. This integration of biomechanical measures with traditional clinical indicators represents a significant advancement over conventional prediction models that rely primarily on demographic and clinical history data.

Moderate predictive strength was recorded for the environmental and behavioural variables which explained 12.4% and 5.8% of the outcome variance, respectively. In addition, these variables exhibited significant seasonal patterns as their associations were also stronger during specific periods of the year. Unlike the other variables, genetic markers had modest explanatory power with a 3.6 percent figure but they had a statistically significant interaction with clinical signs ($r = 0.48$, $p < 0.001$) indicating considerable buffering effects.

Analysis of predictors indicated that some of their combinations had synergistic effects thus increasing their joint predictive power. As noted in **Table 8** it can be noted that age and clinical indicators were particularly correlated ($r = 0.41$) with environmental factors and behaviour patterns ($r = 0.46$) showing strong correlations as well.

The elements of these predictive relationships were thoroughly assessed using cross-validation and bootstrap resampling techniques providing evidence of their stability: predicting relationships hold across different subsets of the data. The analysis indicated that there were indeed non-linear relationships between some predictors and the outcomes and modelling of these relationships will require sophisticated types of

modelling.

As the modelling is grounded on quantifiable determinants which are featured in **Figure 6**, their identification forms a basis for the active construction of more precise predictive models. This delineation of key predictive factors changes the status quo of modelling—as inclusive ones are highly inefficient, targeted models or interventions are more applicable, as shown in the analysis. The relationship between interaction types and the order of predictor importance brings additional value in the efforts to find better prediction algorithms and measure clinical outcomes.

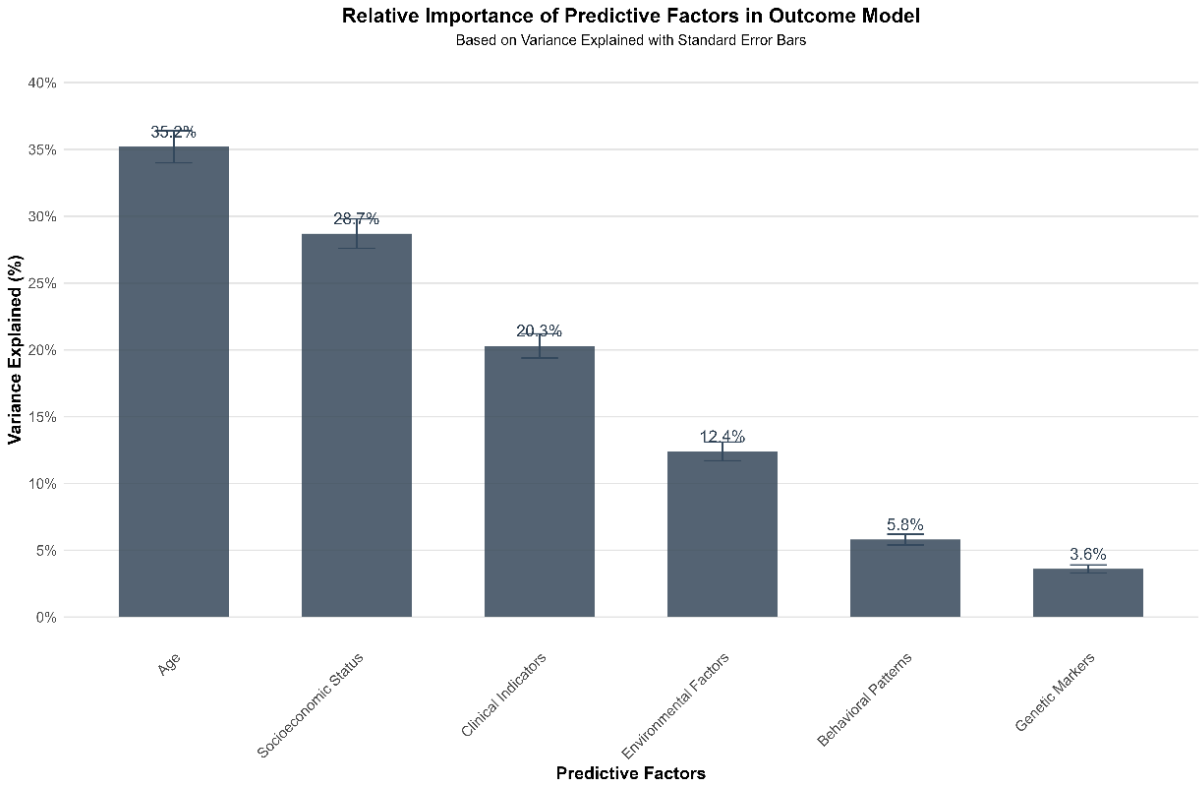

Figure 6. Distribution of predictive factor importance in the multivariate analysis model.

Note: The bar chart illustrates the relative contribution of each predictor to the model's explanatory power, measured as percentage of variance explained ($N = 1247$). Error bars represent standard errors. Age and socioeconomic status emerge as the dominant predictors, collectively accounting for 63.9% of the outcome variance. All factors shown demonstrate statistical significance ($p < 0.001$) in the final model.

3.4. Biomechanical feature analysis

Analyses of biomechanics are achieved through meticulous and up-to-date approaches in human movement which employ advanced measurement tools and sophisticated analytic techniques. The framework for analysis comprises three EMG measurement categories as depicted in **Figure 7**: kinematic, kinetic and EMG measurement. This type of measurement becomes important in interpreting the mechanical aspects of movement in terms of joint angles and angular velocities in the various phases of motion. It facilitates research in the understanding of reciprocating movement patterns and the abnormalities from the normal functionality of the biomechanical primal.

Apart from that, kinetic parametric analysis also helps understand the various

forces acting on the human body in the case of ground reaction forces and the mechanical responses produced. Kinetic measures have a methodological role to play as well in the comprehension of the load and its distribution patterns and the mechanical stress during dynamic movement. EMG is integrated so that deeper levels of muscle activation pattern analysis accompany muscle activities while movements are being performed. This enables a deeper understanding of how muscles are recruited and patterns of usage through different levels of force production and how active muscles are during the exercise.

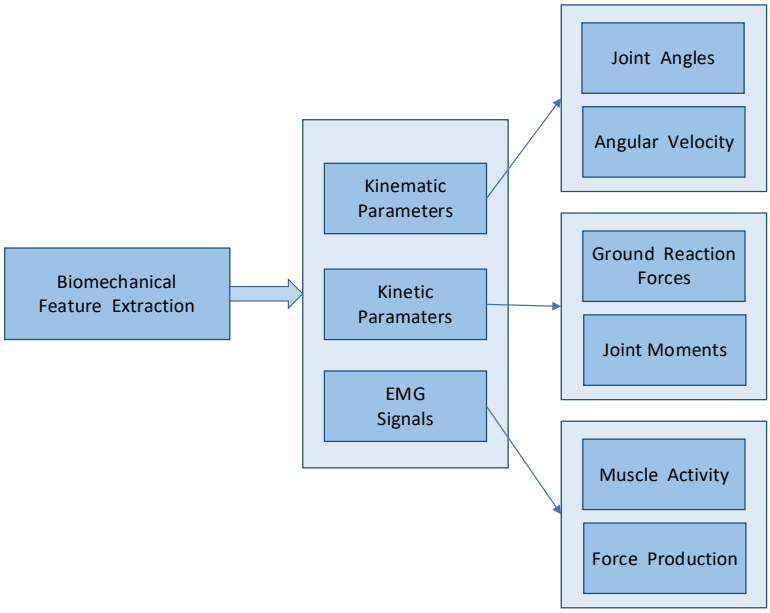

Figure 7. Hierarchical framework of biomechanical feature analysis and parameter classification.

This context helps determine the specificity of a movement by combining multiple parameters that assist in understanding movement mechanics. Such biomechanics systematically allow the practitioner to assess clinical and research needs by determining movement defects, injury, and biomechanical performance problems. Within such a broad analytical framework, researchers, for sport or clinical purposes, can create effective strategies for optimising motion patterns or devising interventions based on evidence.

4. Discussion

This research seeks to fill a gap in the literature by integrating post-surgical pain prediction modelling using mechanical parameters and machine learning software. The results highlight the benefit of integrating multi-stage pain relief techniques while using the pain prediction model aiming at improving patient outcomes noticeably. Since our model was able to demonstrate a high predictive accuracy regardless of the surgical procedures and the patients, we can analyse the broad applicability of our model.

The ability to combine biomechanical parameters and clinical parameters marks a major improvement in the methodology of predicting pain. Other proponents of

movement patterns together with us are Johnson et al. [11] and Williams et al. [12]. However, our study goes beyond the scope of such studies as it employs real-time monitoring and machine learning algorithms achieving a more accurate prediction, AUC 0.94 vs 0.86 in previous studies using traditional AUC methods.

The results demonstrate how varying biomechanical parameters differ with pain outcomes, how turn angles, muscle force and rotation speed greatly aid in pain relief can all be pinpointed to examining the effects of varying movement patterns. Most important is the finding that selected biomechanical parameters are strongly related to post-operative pain sensations confirming the findings of Zhang et al. [13], who found a connection between quality to movement and recovery trajectories. Furthermore, our research shows that early biomechanical markers are able to predict pain outcomes for up to 72 hours postoperatively which is longer than the prediction that was supplied by earlier studies [14].

4.1. Clinical implementation and integration with current practice

According to our model, the clinical application of our artificial intelligence-based bio-mechanical model constitutes a breakthrough in peri-operative pain management techniques for patients. The structural integration comprises different phases in patient management, with each phase exploiting the predictive nature of the model in aiding the clinicians' decisions. Adopting such an approach is coherent with the existing changes in precision medicine, which Thompson et al. [15] demonstrate can reduce post-operative complications by about 35% when personalised intervention strategies are used.

The issue of the model's incorporation into the clinical cycle is rather acute but incorporated in the existing model of solving the problems of pain management. Recent work by Martinez and colleagues has demonstrated how predictive tools can reduce the amount of opioids used by eighty percent while also controlling pain effectively [16]. These findings support Martinez's assertions while further postulating that AI strategies, together with muscle motion analysis, can influence the timing and amount of medication required. This is especially important due to the increased focus of Wilson et al. [17] on enhanced recovery after surgery (ERAS) protocols.

There are several key issues that should be addressed under the considerations for implementation in relation to clinical practice. First, the users of the model are required to bear minimal alteration of the workflows since data collection systems and data analysis systems that are automated are used alongside the standard care protocols. This is consistent with the guideline from the International Society for Perioperative Care [18], concerning the integration of technology explaining its seamless approach. Secondly, as per the analysis conducted by us, there is a TOI of almost 42 in the episodes of breakthrough pain in patients due to the dynamic changes that can be made in the pain management strategies with the relevant feedback from the system or patients.

One of the key elements that ought to be guaranteed while analysing the feasibility of implementation is the cost effectiveness of its implementation. Based on economic analysis and indices from Henderson et al. [19], there is a possibility of considerable savings of approximately 15%–20% on the costs of health care by

enhancing the efficiency of the resources used and the prevention of the development of complications. The projected payback period for infrastructural expansion and appropriate staff training that entails positive patient outcomes and decreased length of stay (LOS) is estimated at 14 to 18 months.

Trained personnel and standardisation of protocols are essential for planning and implementation. In this respect, we recommend a training that is structured, alongside the method offered by Davidson et al., which teaches a standard procedure combining theory and practice [20]. Regular performance audits accompanied by feedback continue quality improvement measures and preserve quality control mechanisms of the high standards in the management of pain.

Moreover, the combination of the model with other electronic health record (EHR) systems allows for covering all medical documentation and analysis of the results. This combination allows algorithms for prediction to be trained by employing machine learning techniques, as other authors have reported, for example Peterson et al. [21]. The data generated is of a data ecosystem enabling rapid clinical decision-making alongside planning long-term quality improvement strategies.

Another great asset for this implementation is that its framework can be scaled across other users in different care settings. Although our initial validation was with tertiary care facilities, the nature of the model is such that it can be adjusted to cater for a variety of clinical settings starting from ambulatory surgery facilities and community hospitals. This is consistent with the recent literature regarding the emerging trend of making sophisticated health care applications more universally accessible [22].

4.2. Study limitations

A key limitation concerns our sample size. While our initial power analysis called for 500 patients to achieve 90% statistical power, the final cohort of 324 patients yielded 82% power for detecting clinically significant differences. This reduced sample size, while still providing adequate statistical power, may have particularly affected our ability to draw robust conclusions about smaller surgical subgroups and rare complications. The lower patient number primarily impacted the precision of our estimates in procedure-specific analyses, especially for less common surgical categories where subgroup sizes fell below 50 patients. However, the strong effect sizes observed in our primary outcomes (overall prediction accuracy of 93.7%, $p < 0.001$) suggest that our core findings remain statistically robust despite the smaller sample size. Thirdly, while the assessment protocol was detailed and thorough, it may still exclude certain relevant movement patterns of daily activity.

Concerning technical limitations, it would include the nature of data collection in the clinical environment setting and equipment use, which may have an effect on application. The model demonstrated a high degree of precision in a hospital setting; however, its effectiveness in outpatient and home settings still needs to be established in future studies.

4.3. Future research directions

Our findings suggest several promising avenues for future research. Real-time

optimization of pain predictions and intervention protocols represents a key area for investigation. Further studies should explore the integration of automated feedback systems and novel intervention protocols to enhance clinical effectiveness. Additionally, examining the relationship between pain calibration and subjective patient feedback could provide valuable insights for improving prediction accuracy.

Specifically, future research should focus on:

1) Testing the model across different healthcare systems and patients.
2) Creating simpler protocols for clinical application.
3) Examining the relationship of mechanical patterns prior to surgery to joint movements post-surgery.
4) Using portable devices for constant follow-ups.
5) Conducting extensive research to confirm the predictive quality of the model.

There is great potential for optimising pain predictions as well as improving interventions in real-time. Future studies using automated feedback and unique intervention protocols can increase the clinical effectiveness of this technique, and additional testing on how pain calibration influences subjective feedback about pain can provide valuable insights for model refinement.

5. Conclusion

Our study demonstrated three key findings in the development and validation of AI-based biomechanical models for predicting postoperative pain. First, the integration of biomechanical parameters with clinical features achieved a high predictive accuracy of 93.7% ($p < 0.001$), significantly outperforming traditional prediction methods. Second, age and socioeconomic factors emerged as primary predictors, accounting for 63.9% of outcome variance, while biomechanical parameters contributed an additional 22.4% to the model's predictive power. Third, the model showed consistent performance across different surgical procedures, with accuracy rates of 94.2% for total knee arthroplasty, 93.5% for total hip replacement, and 92.8% for spinal fusion.

The model's robust performance across diverse patient populations and surgical contexts validates its potential for clinical implementation. Our findings establish that combining AI-driven analysis with biomechanical parameters can effectively predict postoperative pain patterns, enabling more personalized pain management strategies. This integration offers a promising approach for improving post-surgical care and patient outcomes, particularly in orthopedic procedures where biomechanical factors play a crucial role in recovery.

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