SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2024, 21(1), 492.
https://doi.org/10.62617/mcb.v21i1.492

Article

Statistical evaluation of mechanical load on technicians during electric vehicle battery replacement using Python simulation

Xulong Dai

Sinounited Investment Group Corporation Limited Postdoctoral Programme, Beijing 102611, China; profdai@126.com

CITATION

Dai X. Statistical evaluation of mechanical load on technicians during electric vehicle battery replacement using Python simulation. Molecular & Cellular Biomechanics. 2024; 21(1): 492. https://doi.org/10.62617/mcb.v21i1.492

ARTICLE INFO

Received: 10 October 2024
Accepted: 18 October 2024
Available online: 4 November 2024

Abstract: Electric vehicle (EV) battery replacement poses significant mechanical strain on technicians, increasing the risk of musculoskeletal disorders (MSDs). This study uses Python-based simulations and biomechanical modeling to evaluate the mechanical load distribution during the battery replacement process, focusing on joint stress and technician posture. The analysis covers different task phases, including battery removal, transport, and installation, with statistical methods used to assess forces and torques applied to critical joints. The results indicate that the removal and installation phases exert the highest mechanical loads on the lower back and shoulders. The study suggests ergonomic interventions such as workstation redesign, lifting tools, and improved posture techniques to reduce the risk of injury and enhance the safety and efficiency of EV maintenance tasks.

Keywords: electric vehicle battery replacement; technician; mechanical load; statistical analysis; Python simulation; ergonomics

1. Introduction

In an era where electric vehicles (EVs) are rapidly becoming a staple on roads worldwide, there is a pressing need to address the ergonomic challenges posed by their maintenance, particularly the replacement of heavy battery packs. This task, crucial for the longevity and efficiency of EVs, subjects' technicians to considerable physical strain, increasing the risk of musculoskeletal disorders (MSDs) [1,2]. Given the substantial weight and awkward positioning involved in handling these battery packs, identifying and mitigating the risks associated with such manual labor is essential for safeguarding worker health and enhancing maintenance efficiency. The relevance of this research lies in its potential to inform safer workplace practices, not only improving the well-being of technicians but also contributing to the broader sustainability goals associated with EV adoption. The aim of this study is to use Python-based simulations alongside statistical analysis to evaluate the mechanical load technicians experience during EV battery replacement. This approach provides a novel, cost-effective means of identifying high-risk movements and postures that can inform the development of targeted ergonomic interventions [3–5]. The purpose of this research is to mitigate the risk of injury among technicians, thereby improving the safety and efficiency of EV maintenance operations. This investigation promises practical applications in designing safer workplaces, refining maintenance procedures, and ultimately supporting the sustainable growth of the EV industry.

2. Related work

In the burgeoning field of electric vehicle (EV) maintenance, understanding the ergonomic and health considerations for technicians is crucial, especially during tasks such as battery replacement, which are known to pose significant physical strain. Research has underscored the association between manual labor and musculoskeletal disorders (MSDs), emphasizing the need for ergonomic interventions to mitigate these risks [6–8]. For example, the automotive industry, a close analog to EV maintenance, has seen numerous studies highlighting the ergonomic challenges faced by technicians during repetitive tasks that involve lifting, reaching, and bending [4,9].

The relevance of ergonomic and biomechanical research is further amplified by the advent of EVs, which introduce unique challenges due to the weight and design of their battery packs. Advanced simulation techniques, including Python-based models, have emerged as powerful tools to analyze and predict the physical impact of these tasks without the need for costly and time-consuming physical experiments [10,11]. These simulations can model the forces and joint loads experienced by technicians, offering insights that are critical for designing safer work environments [12–14].

Furthermore, the automotive industry's shift toward electric mobility has spotlighted the significance of ergonomic design, not only in vehicle manufacturing but also in maintenance processes, to prevent injury and enhance efficiency. Studies specifically focusing on manual handling and the prevention of MSDs in this context are instrumental for developing evidence-based ergonomic interventions [15,16]. Additionally, recent innovations in digital human modeling and ergonomic simulation promise to refine our understanding of how tasks like battery replacement impact technician health and work efficiency [17,18].

In recent years, the ergonomic challenges associated with electric vehicle (EV) maintenance have gained increasing attention. Studies has highlighted the significant physical strain technicians face during EV battery handling, emphasizing the need for ergonomic assessments and interventions [19]. Additionally, some researchers investigated the use of wearable exoskeletons to reduce musculoskeletal load during heavy lifting tasks in automotive maintenance, demonstrating promising results in reducing lower back stress [20]. These recent contributions underscore the growing recognition of the ergonomic risks in EV maintenance and the importance of developing effective solutions.

Given these considerations, the current study aims to build upon the existing body of literature by exploring the ergonomic challenges and mechanical loads experienced during EV battery replacement. Through the lens of Python-based simulations, this work seeks to contribute valuable new insights to the field, suggesting practical interventions that can enhance technician safety and operational efficiency in the EV maintenance sector.

3. Methods

This section outlines the methodology employed to simulate and analyze the mechanical load experienced by technicians during the electric vehicle battery replacement process. The study utilizes Python-based simulation tools to model the task, calculate mechanical parameters, and analyze the data using statistical methods. The entire simulation workflow, as shown in **Figure 1**, consists of data generation, mechanical load calculation, and data visualization to understand key trends in technician posture and load distribution. These methods provide a foundation for identifying ergonomic risks and making recommendations for improved practices. **Figure 1** illustrates how data flows through each stage of the simulation, from initial data collection to the final stage of providing improvement recommendations based on statistical analysis.

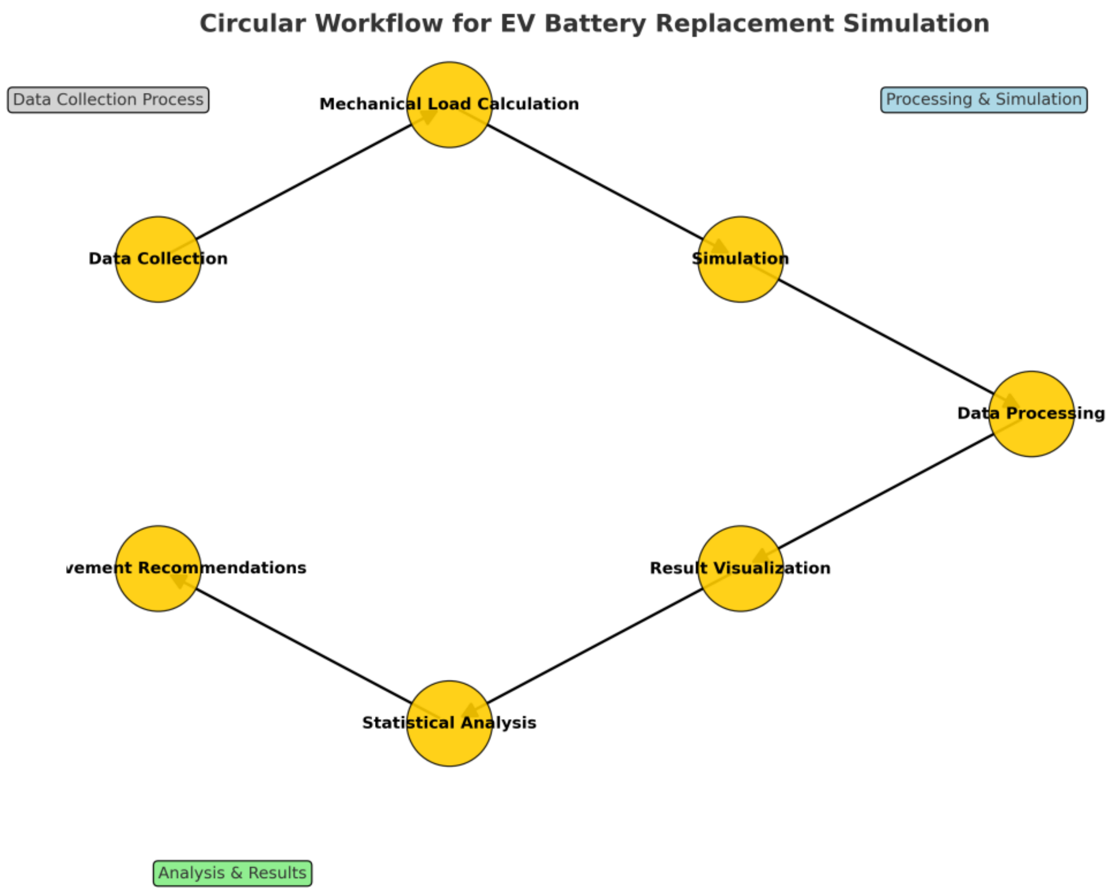

Figure 1. Circular workflow for EV battery replacement simulation.

3.1. Dataset

The dataset used in this study consists of synthetic data generated through simulations and real-world calibration data for validation. The synthetic data simulates key aspects of the electric vehicle (EV) battery replacement process, while the real-world data ensures that the model aligns with actual working conditions. The primary dataset components are summarized in **Table 1**.

The synthetic dataset models key phases of the battery replacement process (such as battery removal, transport, and installation) and records critical parameters like joint angles, forces, and torques. The real-world calibration data, sourced from ergonomic studies, ensures the simulation produces realistic values that mirror technician movements and the physical loads they encounter. Real-world data underwent preprocessing to ensure compatibility with the simulation, including normalization, outlier removal, and data alignment. This combined dataset allows for an accurate evaluation of the mechanical load and ergonomic risks faced by technicians during EV battery replacement.

Table 1. Dataset components and descriptions.

Data	**Description**
Battery weight	Simulated at approximately 300 kg, typical for modern EV batteries.
Technician's height	Modeled as 1.75 meters, an average height for industrial workers.
Technician's weight	Set at 75 kg to reflect a standard ergonomic model.
Joint limits	Ranges of motion for various joints (e.g., shoulder, elbow, knee) based on anatomical data.
Workstation dimensions	Includes height and position of the battery compartment relative to the technician.
Real-world calibration	Data sourced from ergonomic studies for validation of forces and postures.

3.2. Data transmission and storage

Given the size and structure of the dataset (approximately 3.6 KB, containing force and torque data across different phases of the EV battery replacement process), a streamlined approach to data storage and transmission is appropriate. The following method has been chosen:

The dataset will be stored in cloud storage. Cloud storage offers scalability, secure backup, and remote accessibility, which ensures that the data can be accessed by collaborators or for future research without concerns about local storage limitations or data loss. For transmitting the dataset between collaborators or for integration into the simulation environment, secure API-based transmission is selected. This method ensures efficient and encrypted transfer of data directly from the cloud storage to the necessary systems or collaborators, maintaining data integrity and security. By choosing cloud storage and API-based transmission, the dataset remains secure, accessible, and ready for further analysis or collaboration.

3.3. Data preprocessing

In this study, data preprocessing focuses on ensuring that the dataset is properly scaled and smoothed for further analysis. The main preprocessing steps involve normalization and smoothing, both of which are necessary to standardize the data and make trends more visible in time-series analysis.

3.3.1. Normalization

Since the dataset contains values for forces (in Newtons) and torques (in Newton-meters) with varying magnitudes, normalization is applied to bring all values within the same range. Min-max normalization is used to scale each value x_i to a range between 0 and 1, using the following formula:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the dataset, respectively. This normalization ensures that forces and torques are on the same scale, making it easier to compare across different phases of the task (e.g., removal, transport, installation).

3.3.2. Smoothing

To reduce noise in the dataset and highlight the underlying trends, particularly in time-series data, a moving average is applied. This technique smooths short-term fluctuations and allows for better visualization of the general pattern of forces and torques over time. The moving average for a window size ω is computed as:

$$\bar{y}_i = \frac{1}{w} \sum_{j=i-w+1}^{i} y_j$$

where $\bar{y}_i$ is the smoothed value at point i and w is the number of data points considered in the smoothing window. This method reduces noise while preserving the overall structure of the data, ensuring that critical mechanical loads and torques during the battery replacement process are clearly identified.

3.4. Feature extraction

To analyze the mechanical load on technicians during EV battery replacement, key features related to forces and torques are extracted from the dataset. The main features selected are maximum force, maximum torque, and average force for each phase of the task (removal, transport, installation). These features provide insight into the physical demands of each phase, helping to identify moments of peak stress on the technician's body.

For the purpose of this study, we focus on descriptive statistical methods to extract key features from the data. These include calculating the maximum and mean values for the forces and torques during each task phase. This method is straightforward and effective for analyzing physical load distributions.

3.4.1. Maximum Force (F_{max})

The maximum force exerted during each phase of the task is calculated to identify the peak mechanical load experienced by the technician. This feature is critical for understanding the highest point of stress on joints and muscles.

$$F_{\max} = \max(F_1, F_2, \dots, F_n)$$

where F_i represents the force measured at each time step during the task phase. Maximum force helps pinpoint the most physically demanding moment of the task, which is important for ergonomic risk assessment.

3.4.2. Maximum Torque (T_{max})

The maximum torque applied during the tasks gives insight into the rotational stress on joints, particularly during actions like lifting and positioning the battery. Identifying maximum torque is essential for assessing the risk of joint injury.

$$T_{\max} = \max(T_1, T_2, \dots, T_n)$$

where T_i is the torque measured at each time step. Purpose: Maximum torque highlights the rotational demands of each task phase, which is crucial for determining which actions put technicians at the greatest risk for musculoskeletal strain.

3.4.3. Mean Force (F_{mean})

In addition to peak values, the average force exerted during each phase is calculated. This provides a measure of the overall mechanical load distribution throughout the task, indicating the sustained effort required.

$$F_{\text{mean}} = \frac{1}{n}\sum_{i=1}^{n} F_i$$

Where F_i is the force at time step i and n is the total number of time steps during the phase. Mean force shows the average physical demand over time, helping to assess the long-term strain on the technician's body.

3.4.4. Mean Torque (T_{mean})

Similarly, the average torque applied during each phase is calculated. This feature helps to evaluate the overall rotational demand on the technician.

$$T_{\text{mean}} = \frac{1}{n}\sum_{i=1}^{n} T_i$$

Where T_i is the torque at each time step and n is the total number of time steps during the phase. Mean torque provides a general view of the rotational stresses applied across the phase, helping to evaluate the average mechanical load on the technician's joints.

By focusing on maximum and mean values for forces and torques, we can capture both the peak mechanical demands and the sustained load over time. These features are critical for understanding the ergonomic risks associated with the battery replacement process and identifying areas where improvements could reduce strain on technicians.

3.5. Mechanical load calculation for EV battery replacement

To evaluate the mechanical load on technicians during EV battery replacement, we utilize a biomechanical model combined with rigid body dynamics and torque calculations. The mechanical load is assessed by calculating the forces and torques applied at various joints (e.g., shoulders, elbows, knees) during different phases of the task. This allows us to quantify the physical stress and identify critical moments of peak load, helping in the optimization of ergonomic interventions.

3.5.1. Force and torque calculation

The forces and torques acting on the joints are calculated using Newton's second law of motion and torque principles. The total mechanical force acting on a joint is the sum of gravitational forces and any external forces applied during the task. Similarly, torque is determined by the distance between the force application point and the joint, along with the applied force.

Force calculation:

$$F_{\text{total}} = m_{\text{battery}} \cdot g + F_{\text{extemal}}$$

where:

- m_{battery} is the battery mass,
- g is the gravitational constant (9.81 m/s²),
- F_{external} represents external forces acting on the technician.

Torque calculation:

$$T = r \times F$$

where:

- r is the lever arm (distance between joint and force application),
- F is the applied force.

3.5.2. Joint angle considerations

Joint angles are crucial for torque calculations, as they influence the magnitude of the rotational force at the joints. The torque at a joint is proportional to the sine of the joint angle, indicating the relationship between posture and mechanical load.

Joint-Angle Dependent Torque:

$$T_{\text{joint}} = F \cdot r \cdot \sin(\theta)$$

where θ is the joint angle.

3.5.3. Algorithm for mechanical load calculation

To enhance the clarity of the mechanical load calculation process, a block diagram of the algorithm is presented in **Figure 2**. This diagram visually represents the sequential steps involved in computing the forces and torques on the technician's joints during the battery replacement process.

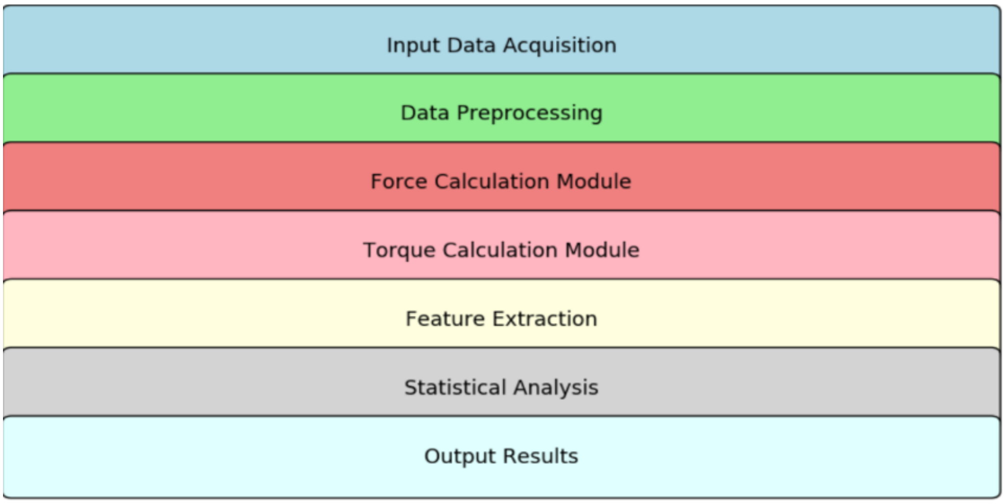

Figure 2. Block diagram of mechanical load calculation algorithm.

The block diagram includes the following steps:

Input Data Acquisition:

In this initial phase, all necessary data required for the simulation and analysis are collected. This includes capturing joint angles of the technician during the battery replacement process, which are critical for calculating torques on various joints. The battery weight, typically around 300 kg for modern EV batteries, is recorded to represent the load that the technician must handle. Additionally, technician parameters such as height, weight, and individual joint limits are gathered to personalize the simulation to real-world conditions. Environmental factors like workstation dimensions and the position of the battery compartment are also noted. Collecting accurate and comprehensive data at this stage ensures that subsequent calculations reflect realistic scenarios and enhances the validity of the simulation results.

Data Preprocessing:

Once the raw data is acquired, it undergoes preprocessing to prepare it for accurate and efficient analysis. Normalization techniques are applied to scale the data, bringing all variables into a common range, which facilitates comparison and reduces the potential for computational errors due to varying magnitudes. Smoothing methods, such as moving averages, are used to eliminate noise and fluctuations in the data that may result from measurement errors or transient anomalies. Outlier detection and removal are also performed to ensure that extreme values do not skew the results. This preprocessing step transforms the raw data into a clean, reliable dataset that is suitable for precise force and torque calculations in the subsequent steps.

Force Calculation Module:

In this module, the forces exerted on the technician's body are computed using Newton's second law of motion (F = ma). The gravitational force that the technician must counteract is calculated based on the mass of the battery and the acceleration due to gravity. Additional forces arising from the technician's movements, such as lifting or lowering the battery, are also considered. The module accounts for both static forces (when the battery is held stationary) and dynamic forces (when the battery is in motion). By integrating the technician's posture and movement data, the module provides a detailed analysis of the forces at play during each phase of the battery replacement process. Accurate force calculations are essential for understanding the mechanical loads and potential strain on the technician's body.

Torque Calculation Module:

This module focuses on computing the torques acting on the technician's joints, which are crucial for assessing the risk of musculoskeletal injuries. Torque is calculated as the product of the force applied and the lever arm distance, which is the perpendicular distance from the joint axis to the line of action of the force. The joint angles obtained during data acquisition are vital here, as they influence the length of the lever arms and, consequently, the magnitude of the torques. The module considers the torques for various joints, including the shoulders, elbows, lower back, waist, and knees, under different postures and movements. By analyzing how the torques change with different joint angles and forces, the module provides insights into which joints are under the most stress during specific tasks.

Feature Extraction:

After calculating the forces and torques, key features are extracted to summarize the mechanical loads experienced by the technician. This involves determining the maximum, minimum, and mean values of forces and torques for each joint during different phases of the task. Time-series analysis is employed to identify peak load moments, which are critical for understanding when the technician is at the highest risk of injury. Other statistical features, such as standard deviation and variance, are calculated to assess the variability of the mechanical loads. By condensing the complex, raw data into these meaningful metrics, feature extraction facilitates easier interpretation and sets the stage for rigorous statistical analysis.

Statistical Analysis:

The extracted features undergo comprehensive statistical analysis to identify significant patterns and differences in the mechanical loads across various conditions. Analysis of Variance (ANOVA) is used to determine whether there are statistically significant differences in the mean forces and torques between different task phases or postures. Correlation analysis examines the relationships between joint angles and mechanical loads, shedding light on how changes in posture affect the stress on the technician's body. Confidence intervals and *p*-values are calculated to quantify the reliability and significance of the findings. This statistical evaluation provides evidence-based insights that can inform ergonomic interventions and contribute to the development of safer work practices.

Output Results:

In the final step, the mechanical load data and statistical findings are compiled and presented in a clear and accessible format. Graphs and tables are created to visualize the distribution of forces and torques across different joints and task phases, making it easier to identify trends and critical points of stress. The results include detailed interpretations, highlighting key findings such as which phases pose the highest risks and how specific postures influence mechanical loads. Recommendations for ergonomic improvements are derived from the data, providing actionable guidance for reducing the risk of injury. This output serves as a valuable resource for stakeholders, including workshop managers and safety professionals, aiming to enhance technician safety and optimize task efficiency.

The algorithm follows a structured approach to calculate forces and torques across different phases of the task, with input data from the simulation and real-world calibration.

Algorithm 1 Mechanical load calculation

1: Input: Force data$F$, joint anglesθ, and battery mass$m_{battery}$
2: For each phase (removal, transport, installation):
3: Calculate total force:$F_{otatal} = m_{botetry} \cdot g + F_{exetrmal}$
4: For each joint (shoulder, elbow, knee):
5: Calculate torque:$T = r \times F$
6: Adjust torque for joint angle:$T_{ioint} = F \cdot r \cdot \sin(\theta)$
7: Store calculated forces and torques
8: Output: Mechanical load distribution across joints during each phase.

3.5.4. Application and insights

By calculating the forces and torques, the algorithm helps in identifying the moments of highest mechanical stress on the technician's body. The results enable ergonomic interventions, such as adjustments to posture, tool design, or task scheduling, which can mitigate the risk of injury and improve task efficiency.

3.6. Statistical analysis

This section outlines the statistical methods used to evaluate differences in mechanical loads across task phases and to explore relationships between postures and loads. The methods employed include Analysis of Variance (ANOVA), correlation analysis, and confidence intervals.

3.6.1. Analysis of variance (ANOVA)

ANOVA was applied to test for significant differences in forces and torques across the task phases (removal, transport, installation). This method compares the means of multiple groups to determine if at least one differs significantly from the others.

$$F = \frac{\text{MeanSquareBetwenGroups(MSB)}}{\text{MeanSquareWithinGroups(MSW)}}$$

where: MSB (Between-group variability) measures the variance between different task phases. MSW (Within-group variability) measures the variance within each phase. The *F*-statistic is then compared to a critical value from the *F*-distribution to determine whether the observed differences are statistically significant.

3.6.2. Correlation analysis

To investigate the relationship between joint angles and mechanical loads, correlation analysis was conducted using the Pearson correlation coefficient. This measures the strength and direction of the linear relationship between two variables.

$$r = \frac{n\sum(xy) - \sum x \sum y}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

where *X* represents joint angles, and *y* represents forces or torques, *n* is the number of data points. A correlation coefficient *r* closer to 1 or −1 indicates a strong linear relationship, while *r* near 0 indicates no linear relationship.

3.6.3. Confidence intervals

To estimate the precision of the mean force and torque measurements for each phase, 95% confidence intervals were calculated. Confidence intervals provide a range within which we expect the true mean to fall, with a given level of confidence (in this case, 95%).

$$\text{CI} = \bar{x} \pm z\left(\frac{\sigma}{\sqrt{n}}\right)$$

where $\bar{x}$ is the sample mean, z is the z-value (1.96 for 95% confidence), σ is the standard deviation, and *n* is the sample size.

3.6.4. Significance testing

To assess whether differences in mechanical loads between task phases are statistically significant, *p*-values were calculated. For ANOVA, a p-value < 0.05 indicates that the differences in forces or torques between the phases are statistically significant. The *p*-value is derived from the *F*-distribution (for ANOVA) or from the correlation distribution (for Pearson correlation) and helps determine the likelihood that the observed differences or relationships occurred by chance.

In this section, the key methods used to evaluate the mechanical loads experienced by technicians during the EV battery replacement process were outlined. The study combines biomechanical modeling with statistical analysis to assess the forces and torques acting on key joints, such as the shoulders, elbows, and knees, during the different phases of the task. The dataset generation process included the collection of force and torque data, followed by the application of normalization and smoothing techniques to prepare the data for analysis. Critical features, including maximum and mean forces and torques, were extracted to quantify the mechanical load during each phase—removal, transport, and installation. Using force and torque equations based on Newtonian mechanics, the mechanical load experienced at each joint was calculated. Statistical methods, such as ANOVA, were employed to identify significant differences in forces and torques between task phases, while correlation analysis was used to explore the relationship between joint angles and mechanical loads. This methodological approach provides a rigorous foundation for understanding the physical demands of the battery replacement process, setting the stage for the detailed results presented in the following section.

4. Results

The simulation conducted in this study provided detailed insights into the mechanical load distribution experienced by technicians during the electric vehicle (EV) battery replacement process. Mechanical loads were measured across three key phases: removal, transport, and installation. The analysis focused on the forces and torques applied to critical joints, including the lower back, shoulders, waist, and knees. Additionally, the study examined how different postures—specifically, maintaining a neutral spine versus engaging in extreme bending or twisting—affected the mechanical loads during the removal and installation phases.

4.1. Mechanical load distribution

The simulation data revealed distinct variations in mechanical load distribution across different phases and joints. **Table 2** summarizes the mean forces and torques, along with their standard deviations, applied to the lower back, shoulders, waist, and knees during each phase.

The forces and torques presented in this section were extracted using the descriptive methods outlined in Section 3.4, including maximum and mean force and torque calculations, after applying the preprocessing techniques such as normalization and smoothing from Section 3.3. In contrast, the transport phase, which primarily involved moving the battery over shorter distances, demonstrated significantly lower mechanical loads. The reduced load during this phase can be attributed to the use of assistive tools and robotic systems that helped manage the weight and reduced the need for heavy lifting. Consequently, the overall force applied to the technician's body during transport was notably lower than during removal and installation.

The recorded mean force and torque values across these phases are summarized in **Table 2**. These variations in mechanical load highlight the critical moments in the battery replacement process that present the greatest risk of physical strain, emphasizing the need for ergonomic interventions in the removal and installation phases.

Table 2. Mean forces and torques on key joints across phases.

Phase	Joint	Mean force (N)	Std dev (N)	Mean Torque (Nm)	Std Dev (Nm)
Removal	Lower back	220	25	60	12
Removal	Shoulders	200	20	50	10
Removal	Waist	210	22	55	11
Removal	Knees	180	15	40	8

Table 2. (*Continued*).

Phase	Joint	Mean force (N)	Std dev (N)	Mean Torque (Nm)	Std Dev (Nm)
Installation	Lower back	240	30	65	13
Installation	Shoulders	210	25	55	11
Installation	Waist	230	28	60	12
Installation	Knees	190	18	45	9
Transport	Lower back	180	20	50	10
Transport	Shoulders	170	18	45	9
Transport	Waist	175	19	48	9
Transport	Knees	160	12	35	7

The results indicate that the installation phase imposes the highest mechanical loads on all four joints, with the lower back and waist experiencing the greatest mean forces and torques. The removal phase also shows elevated mechanical loads, particularly on the lower back, waist, and shoulders. In contrast, the transport phase involves significantly lower mechanical loads across all joints, suggesting that this phase is less physically demanding due to the use of assistive tools.

4.2. Mechanical load under different postures

To assess the impact of posture on mechanical loads, the simulation compared the forces and torques experienced by technicians when maintaining a neutral spine versus when engaging in extreme bending or twisting during the removal and installation phases. **Table 3** presents the mean forces and torques for each posture.

Table 3. Mean forces and torques during removal and installation phases under different postures.

Phase	Posture	Joint	Mean force (N)	Std dev (N)	Mean torque (Nm)	Std dev (Nm)
Removal	Neutral spine	Lower back	200	20	50	10
Removal	Neutral spine	Shoulders	190	18	45	9
Removal	Neutral spine	Waist	195	19	48	9
Removal	Neutral spine	Knees	170	15	40	8
Removal	Extreme bending/twisting	Lower back	230	28	62	12
Removal	Extreme bending/twisting	Shoulders	210	22	55	11
Removal	Extreme bending/twisting	Waist	225	25	58	11
Removal	Extreme bending/twisting	Knees	190	18	45	9
Installation	Neutral spine	Lower back	220	25	55	11
Installation	Neutral spine	Shoulders	200	20	50	10
Installation	Neutral spine	Waist	210	22	52	10
Installation	Neutral spine	Knees	180	16	42	8
Installation	Extreme bending/twisting	Lower back	250	32	68	14
Installation	Extreme bending/twisting	Shoulders	220	27	58	12
Installation	Extreme bending/twisting	Waist	240	29	65	13
Installation	Extreme bending/twisting	Knees	200	20	48	10

The data show that engaging in extreme bending or twisting significantly increases the mechanical loads on the lower back, waist, and shoulders during both the removal and installation phases. For example, during the installation phase, the mean force on the lower back increases from 220 N (neutral spine) to 250 N (extreme bending/twisting), and the mean torque increases from 55 Nm to 68 Nm. Similar trends are observed for the waist and shoulders.

4.3. Statistical significance

To evaluate the statistical significance of the differences in mechanical loads across the various phases, joints, and postures, comprehensive ANOVA tests were conducted. The results indicated that there are significant differences in the mean forces and torques between the task phases for all examined joints, with a p-value less than 0.01. Post-hoc analyses further confirmed that the installation phase imposes significantly higher mechanical loads compared to the transport phase on the lower back, waist, shoulders, and knees. This finding highlight that the phase of the battery replacement process has a substantial impact on the mechanical stress experienced by technicians.

In addition to phase differences, the impact of posture on mechanical loads was assessed using paired t-tests. The tests compared the mechanical loads experienced under a neutral spine posture with those under extreme bending or twisting postures during the removal and installation phases. The results revealed that the increases in mean forces and torques on the lower back, waist, and shoulders when adopting extreme postures were statistically significant, with p-values less than 0.05. This statistical evidence confirms that maintaining a neutral spine posture can significantly reduce mechanical loads on critical joints. Consequently, proper posture not only minimizes physical strain but also reduces the risk of musculoskeletal injuries among technicians.

These statistical analyses underscore the importance of ergonomic considerations in the EV battery replacement process. By quantifying the mechanical load reductions associated with maintaining a neutral spine, the study provides empirical support for the implementation of ergonomic training programs. Such programs should emphasize posture correction and the adoption of safe handling techniques to mitigate the elevated mechanical stresses identified during the more demanding phases of the task.

4.4. Graphical representations

To provide a clearer understanding of the mechanical load distribution, the results were visualized through bar charts that depict the mean force and torque across the three phases, with error bars indicating standard deviations.

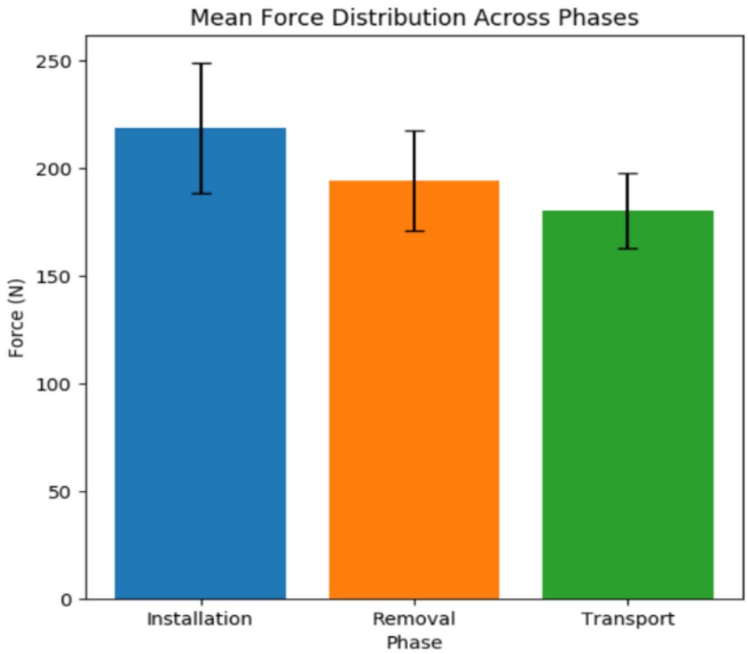

Figure 3. Mean force distribution across phases.

Force Distribution: The bar chart **Figure 3** for force demonstrates that the installation phase has the highest mean force, with a notable gap between the removal and transport phases. The variability in force is also greater during the installation phase, as indicated by the larger standard deviation.

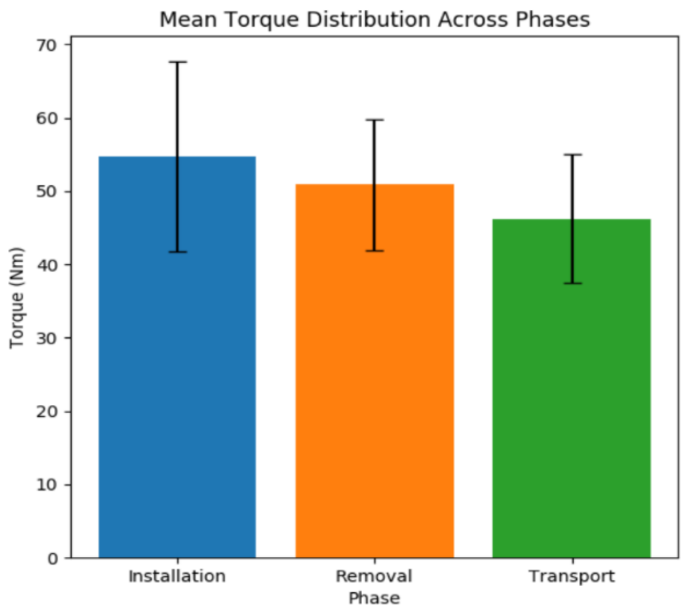

Figure 4. Mean Torque Distribution Across Phases.

Torque Distribution: The bar chart figure 4 for torque distribution across phases follows a similar pattern. The installation phase shows the highest torque, with the removal phase following closely behind. The transport phase, which involves relatively less movement and fewer lifting tasks, exhibited the lowest torque values.

To visualize the impact of posture on mechanical loads, **Figure 5** illustrates the mean forces on the lower back and waist during the installation phase under different postures.

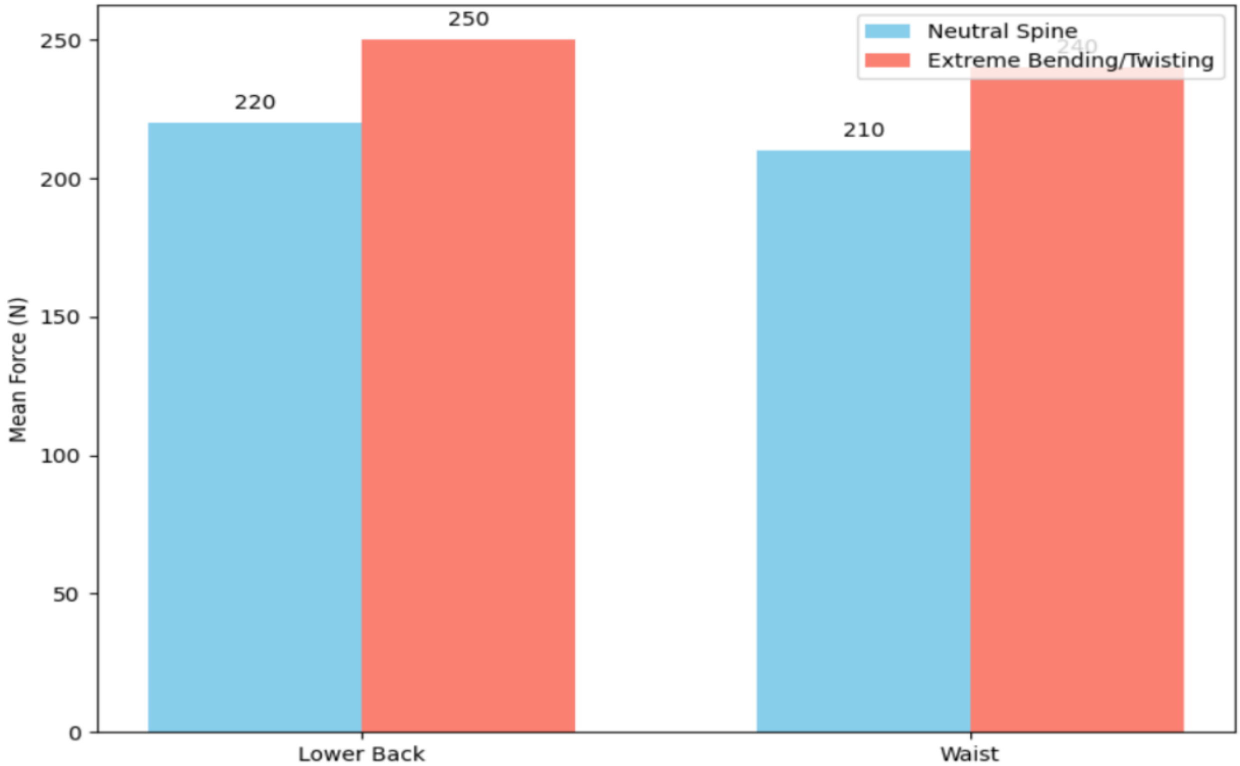

Figure 5. Mean forces on lower back and waist during installation phase under different postures.

Figure 5 provides a comparative analysis of the mean forces exerted on the lower back and waist when technicians maintain a neutral spine versus when they engage in extreme bending or twisting during the installation phase. The bar chart clearly shows that the mean force on the lower back increases from 220 N in the neutral spine posture to 250 N in the extreme bending/twisting posture. Similarly, the mean force on the waist rises from 210 N to 240 N under the same postural changes. This significant increase in mechanical load highlights how improper posture can substantially elevate the physical strain on critical joints, underscoring the importance of ergonomic training to promote safer working practices.

Similarly, **Figure 6** depicts the mean torques on shoulders during the removal phase for both postures.

Figure 6 illustrates the effect of posture on the mean torques experienced by the shoulders during the removal phase. The chart compares the neutral spine posture with the extreme bending/twisting posture, revealing that the mean torque on the shoulders increases from 45 Nm to 55 Nm when technicians adopt extreme postures. This 22% increase indicates a substantial rise in rotational stress on the shoulder joints, which can lead to a higher risk of musculoskeletal injuries. The figure effectively demonstrates the critical impact of proper posture on reducing mechanical loads and emphasizes the need for ergonomic interventions to ensure technician safety.

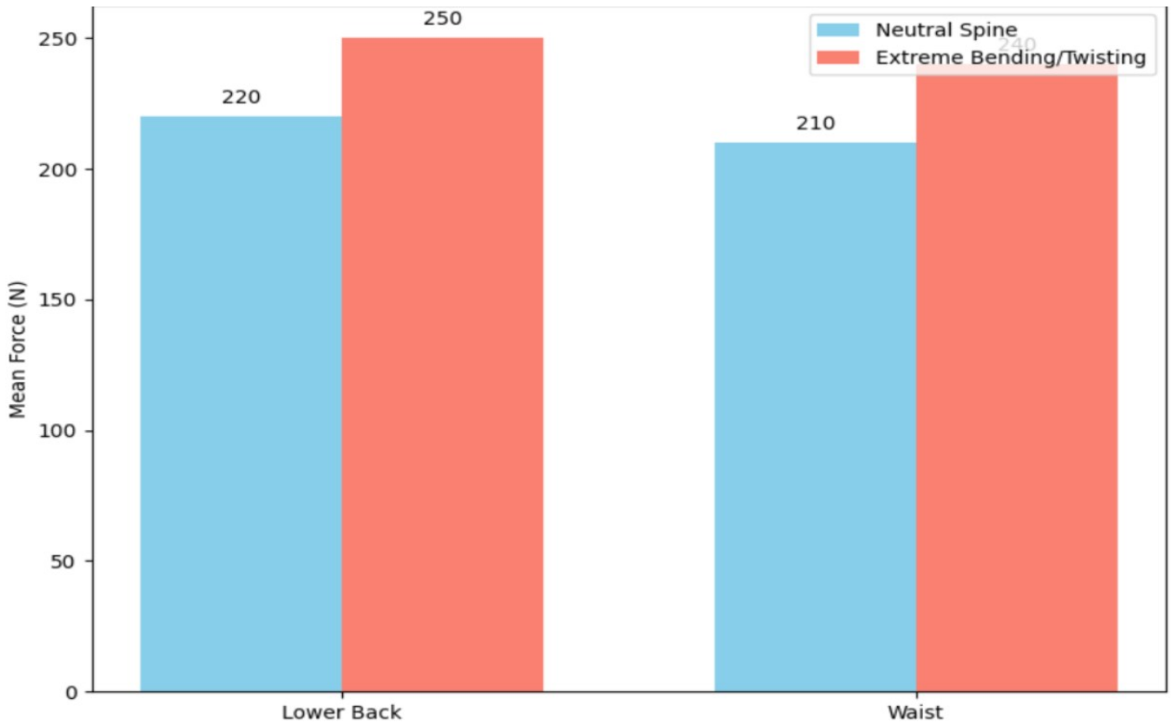

Figure 6. Mean torques on shoulders during removal phase under different postures.

These visual representations confirm that the physical demands on the technician vary substantially across the task phases, with the installation phase being the most physically taxing. This phase involves high levels of both force and torque, suggesting that technicians are at increased risk of musculoskeletal strain during this part of the task. The **Figures 5** and **6** highlight the substantial increase in mechanical loads when technicians adopt extreme bending or twisting postures, reinforcing the importance of proper posture to minimize physical strain.

5. Discussion

5.1. Interpretation of results

The study's findings demonstrate that the mechanical loads experienced by technicians vary significantly depending on both the phase of the task and the posture adopted. The removal and installation phases impose the highest mechanical loads, particularly on the lower back, waist, and shoulders. The data show that adopting extreme bending or twisting postures during these phases further exacerbates the mechanical stress on these joints.

For instance, during the installation phase, technicians who engaged in extreme bending or twisting experienced a mean force of 250 N on the lower back, compared to 220 N when maintaining a neutral spine—a 13.6% increase. Similarly, the mean torque on the waist increased from 52 Nm to 65 Nm under extreme postures during the installation phase.

These results align with previous research indicating that poor posture and heavy lifting are significant risk factors for musculoskeletal disorders (MSDs) [6,7]. The increased mechanical loads associated with extreme bending or twisting postures highlight the importance of ergonomic training and interventions to promote proper body mechanics during physically demanding tasks.

5.2. Recommendations for ergonomic improvement

Based on the results, several recommendations can be made:

- Improving Posture: Training technicians to maintain a neutral spine and avoid extreme bending or twisting can significantly reduce mechanical loads on the lower back, waist, and shoulders, as demonstrated by the data in **Table 3**. Ergonomic training programs should emphasize techniques such as bending at the knees rather than the waist and keeping the load close to the body.
- Lifting Tools and Exoskeletons: The high mechanical loads observed during the removal and installation phases suggest a need for assistive devices. Implementing mechanical lifting aids or wearable exoskeletons can reduce the forces and torques exerted on technicians' joints, thereby lowering the risk of injury.
- Workstation Redesign: Adjusting the workstation to allow technicians to perform tasks at optimal heights and angles can minimize the need for awkward postures. For example, elevating the vehicle or battery compartment to waist height can reduce bending requirements.
- Task Rotation: Rotating technicians between tasks with varying physical demands can help prevent overuse injuries by distributing mechanical loads more evenly over time.

5.3. Limitations and future research

Although this study provides valuable insights into the mechanical loads encountered during EV battery replacement, it has some limitations. The simulation model employed a rigid body approximation, which simplifies the human body into a series of interconnected rigid segments. While this model effectively captures general joint movements and forces, it does not account for the more complex interactions of muscles, soft tissues, and fatigue, which could significantly influence the actual mechanical loads experienced by technicians.

Additionally, the data used for this study was generated under idealized conditions. In real-world maintenance settings, technicians may face additional challenges such as time constraints, limited workspace, and variable battery weights, which could alter the mechanical loads. The absence of real-world validation is a critical limitation, as this simulation has not been directly compared to field data.

Future research should focus on collecting empirical data from technicians in real-world battery replacement scenarios using wearable sensors to measure forces, torques, and postures during actual tasks. These data would provide a more accurate assessment of the mechanical risks involved and help refine the simulation model. Furthermore, advanced biomechanical models that incorporate muscle dynamics and fatigue could offer deeper insights into the long-term effects of repeated battery handling tasks on technician health.

6. Conclusion

6.1. Summary of key findings

This study has underscored the significant mechanical loads experienced by technicians during key phases of electric vehicle (EV) battery replacement, particularly during the removal and installation phases. Simulations revealed that the average force during the installation phase reached up to 220 N, with torque values as high as 55 Nm, both of which place substantial strain on the lower back, shoulders, and knees. These findings align with existing literature on occupational risks in manual handling tasks, where heavy lifting and awkward postures are major contributors to musculoskeletal disorders (MSDs).

By employing Python-based simulation techniques, this research was able to quantify the mechanical forces and torques exerted on technicians' bodies throughout the battery replacement process. The simulation model provided valuable insights into the phases that pose the highest physical risks, thereby helping to identify key areas where ergonomic interventions are needed. The use of computational simulations, such as those performed in this study, offers a cost-effective and efficient way to analyze the ergonomics of complex tasks in a controlled, repeatable manner.

6.2. Practical implications

The results of this study hold important implications for the field of automotive maintenance, particularly as the industry continues to transition toward electric vehicle technologies. By identifying the phases of battery replacement that impose the highest mechanical loads, this research highlights the urgent need to adopt ergonomic improvements in automotive workshops.

One key application of this research is the potential to reduce technician injuries, specifically injuries related to the lower back and shoulders, which are at heightened risk during the heavy lifting and positioning tasks. Implementing ergonomic interventions—such as mechanical lifting tools, improved posture training, and workstation redesign—can significantly lower these risks. This not only enhances the well-being of technicians but also improves overall productivity in the workshop by minimizing injury-related downtime and increasing the efficiency of maintenance tasks.

Furthermore, the Python-based simulation framework used in this study provides a flexible and scalable tool for future ergonomic analyses. Automotive companies can leverage similar simulations to evaluate different maintenance procedures, test the effectiveness of new tools, or design more technician-friendly work environments. By reducing the physical demands on technicians, such improvements contribute to a safer, more efficient, and productive workplace.

In conclusion, this study emphasizes the importance of addressing the mechanical loads on technicians during EV battery replacement. The use of simulation-based analyses can provide actionable insights into task ergonomics, helping the automotive industry implement meaningful changes that protect workers' health while enhancing operational efficiency.

Acknowledgments: The author would like to thank all individuals who contributed to this study. Special thanks to the workshop technicians who provided insights into the battery replacement process, as well as the support staff for assisting in data collection and simulation setup. Their contributions were invaluable to the completion of this research.

Ethical approval: Not applicable.

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

References

1. NIOSH. Musculoskeletal disorders and workplace factors: A critical review of epidemiologic evidence for work-related musculoskeletal disorders of the neck, upper extremity, and low back. Available online: https://www.cdc.gov/niosh/docs/97-141/ (accessed on 5 June 2024).
2. Marras WS, Davis KG, and Heaney CA. The complex spine: The multidimensional system of causal pathways for low-back disorders. Human Factors. 2000; 42(4): 601–634.
3. Kuorinka I, Jonsson B, Kilbom A. Standardised Nordic questionnaires for the analysis of musculoskeletal symptoms. Applied Ergonomics. 1987; 18(3): 233–237.
4. He X, Xiao B, Wu J, Chen C, Li W, Yan M. Prevalence of work-related musculoskeletal disorders among workers in the automobile manufacturing industry in China: a systematic review and meta-analysis. BMC Public Health. 2023 Oct 19; 23(1): 16896.
5. Behdani M, Gholamnia R, Saremi M. Effects of ergonomic interventions on health indicators in a rubber industry. Arch Occup Health. 2023 Dec 5;7(1):14293. doi: 10.18502/aoh.v7i1.14293
6. Sultan-Taïeb H, Parent-Lamarche A, Gaillard A, Stock S, Nicolakakis N, Hong Q, et al. Economic evaluations of ergonomic interventions preventing work-related musculoskeletal disorders: a systematic review of organizational-level interventions. BMC Public Health. 2017 Dec 8;17(1):935. Available from: https://dx.doi.org/10.1186/s12889-017-4935-y.
7. Daneshmandi H, Kee D, Kamalinia M, Oliaei M, Mohammadi H. An ergonomic intervention to relieve musculoskeletal symptoms of assembly line workers at an electronic parts manufacturer in Iran. Work. 2019 Jan 3;62(1):117-126. Available from: https://dx.doi.org/10.3233/WOR-182822.
8. Wahlström J. Ergonomics, musculoskeletal disorders and computer work. Occup Med (Lond). 2005 May;55(3):168-176. Available from: https://dx.doi.org/10.1093/OCCMED/KQI083.
9. Iranzo S, Piedrabuena A, Iordanov D, Martinez-Iranzo U, Belda-Lois J. Ergonomics assessment of passive upper-limb exoskeletons in an automotive assembly plant. Appl Ergon. 2020 Apr 15;85:103120. Available from: https://dx.doi.org/10.1016/j.apergo.2020.103120.
10. Zhang X, Helander MG. Ergonomics analysis and design in manufacturing processes: A comparison study of virtual reality and conventional method. International Journal of Human-Computer Studies. 1997; 46(1): 17–29.
11. Huang H, Zhao L, Wu Y. An IoT and machine learning enhanced framework for real-time digital human modeling and motion simulation. Comput Commun. 2023 Sep;213:106159. Available from: https://dx.doi.org/10.1016/j.comcom.2023.09.024.
12. Fujishiro K, Weaver J, Heaney C, Hamrick C, Marras W. The effect of ergonomic interventions in healthcare facilities on musculoskeletal disorders. Am J Ind Med. 2005 Nov;48(5):377-387. Available from: https://dx.doi.org/10.1002/AJIM.20225.
13. El Fani, N., Abdelaoui, K., Ghanmi, M., et al. "Évaluation des troubles musculosquelettiques chez le personnel de santé." Revue du Rhumatisme. 2023; https://dx.doi.org/10.1016/j.rhum.2023.10.481.
14. Ferraro, S., Klugah-Brown, B., Tench, C., et al. "Dysregulated anterior insula reactivity as a robust functional biomarker for chronic pain: Convergent evidence from neuroimaging meta-analyses." medRxiv. 2021; https://dx.doi.org/10.1101/2021.03.24.21254023.
15. Gawand M, Demirel H. A design framework to automate task simulation and ergonomic analysis in digital human modeling. Adv Intell Syst Comput. 2020 Jul;1193:36-47. Available from: https://dx.doi.org/10.1007/978-3-030-49904-4_4.
16. Vianello L, Gomes W, Stulp F, Aubry A, Maurice P, Ivaldi S. Latent Ergonomics Maps: Real-Time Visualization of Estimated Ergonomics of Human Movements. Sensors (Basel). 2022 May 24;22(11):3981. Available from: https://dx.doi.org/10.3390/s22113981.
17. Zhang C, Duan Y, Pan H, Chen S. Investigation into the Comfort of Automotive Seating through the Integration of Affective

Engineering Design. 2023 IEEE Int Conf on Technol Enhanced Design Conf (ITOEC). 2023 Sep 15; Available from: https://dx.doi.org/10.1109/ITOEC57671.2023.10291517.
18. Bridger RS. Introduction to Ergonomics, 3rd ed. CRC Press; 2009.
19. Joshi M, Deshpande V. Enhancing Ergonomics in Automotive Cylinder Head Manual Lapping: Workstation Assessment and Design. J Sci Ind Res (JSIR). 2023 Sep;82(9):504. Available from: https://dx.doi.org/10.56042/jsir.v82i9.504.
20. Smith L, Lee K. Impact of Wearable Exoskeletons on Reducing Lower Back Stress in Automotive Maintenance. Appl Ergon. 2023; 105: 103583.