

Article

Explaining Ergonomic Dynamics via Robust Syntropy

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Abstract

Musculoskeletal injuries constitute a critical industrial challenge, yet predictive ergonomic methodologies have remained largely stagnant. Conventional assessments are primarily limited to static, linear snapshots of posture, resulting in a failure to capture the inherently dynamic and chaotic nature of human movement over time. To address this limitation, the present study introduces an innovative approach grounded in nonlinear dynamical systems and robust statistics. The objective was to determine whether information-theoretic and dynamic metrics, specifically Shannon Entropy and the Largest Lyapunov Exponent (LyE), can accurately quantify the structural stability of the cervical spine during a fatigue-inducing isometric protocol. To mitigate the inherent noise of field-derived biomechanical data and prevent algorithmic singularities during phase-space reconstruction, zero-phase Butterworth filtering as well as uniform Gaussian noise injection (Gaussian dither) were systematically applied. The analysis revealed a clear, quantifiable topological shift: as localized muscular fatigue accumulates, the biomechanical system abruptly transitions from a state of stable, organized kinematic flow directly into chaotic instability. Furthermore, these interpretable nonlinear metrics demonstrate high suitability for integration into Explainable Artificial Intelligence (XAI) safety architectures. By transforming complex, stochastic biomechanical data into clear diagnostic biomarkers, this research establishes a foundational framework for proactive, real-time preventive safety measures, thereby advancing the paradigm of Syntropic Bioergonomics.

Keywords: ergonomics; nonlinear dynamical systems; explainable AI (XAI); robust statistics; biomimicry; syntropic bioergonomics



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1. Introduction

1.1. The Evolution Toward Human-Centric Systems

Industry 4.0 was primarily related to efficiency and automation. Now, Industry 5.0 focuses more on the human factor and the improvement of the worker's working conditions. The goal is to manage to have humans and machines operate in harmony, using smart systems to enhance our creativity instead of simply replacing our labor [1]. Healthcare 5.0 is a particularly satisfactory example of this shift, as it creates a digital space where advanced cyber-physical systems continuously monitor our physical states [2].

By integrating data analytics, healthcare deepens on a personal level. We can now use real-time data from wearable sensors to manage individual health [3,4]. Big data predictive analytics allow us to identify warning signs in historical and daily workflows,

thus preventing adverse health events [5]. These real-time systems bridge the detection of a problem and its treatment, offering clinical support exactly when needed [6,7].

Unfortunately, there is a massive gap in how we handle and evaluate ergonomic load. Traditionally, ergonomics is treated as a static checklist, whereas we should start treating it as a dynamic control problem [8]. Ergonomic load must be treated as a continuously evolving parameter embedded directly into the human–machine loop. Architectures like the Dynamic Integrity Governor (DIG) demonstrate the actual operational viability of this concept [9]. To manage the unpredictable nature of human movement in high-risk environments, the shift from passive monitoring of musculoskeletal safety to active closed-loop protection is important [10,11]. It is therefore of crucial importance to define a new field of research for the maintenance of structurally and kinematically stable human–machine interactions through linear dynamics, Syntropic Bioergonomics.

1.2. Limitations of Conventional Ergonomic Assessments

Quantitative gait analysis constitutes the first clinical movement monitoring, where it contributed successfully to the treatment of neuromuscular disorders [12,13]. Today's complex musculoskeletal models serve researchers in predicting surgical outcomes by monitoring joint forces and muscle firing [14]. However, the tools with which we evaluate safety in the workplace are confined to static snapshots of the worker's posture. One such tool is the Rapid Entire Body Assessment (REBA), which is ideal for a quick risk check; nevertheless, it lacks the stochastic nature of fatigue, since it cannot monitor how much time a posture is maintained or the cumulative damage from small, repetitive strains [15].

Older models also try to simulate the body using discrete masses and springs. The said lumped-parameter approach cannot accurately simulate a continuous biological body [16]. Its mechanics give us a much better picture and prove that actions such as walking are not simply top-down brain commands; they are low-frequency physical functions embedded in the physical structure of our body [16]. Soft tissues make the process more complex. You absolutely need hyperelastic laws to model them correctly, because biological stress and strain do not scale in a straight line [17].

We have known the basic rules of movement for decades [18]. The real issue is that attaching sensors to a body sometimes modifies how the person moves. These measurement artifacts can easily trick us and hide the subtle ways in which the body reprograms its locomotion patterns [19].

The attempt to determine these discrete biological states is full of uncertainty, just like the attempt to quantify an information source using entropy [20]. To overcome these hurdles, we need a new framework. We must combine the nonlinear behavior of the hyperelastic tissue with strong statistical metrics that can truly measure stability inside moving trajectories.

1.3. The Mathematical Foundations

The depiction of the stability of human movement using straight lines is infeasible; conversely, it is clear that we must turn to dynamic trajectories in the phase space that move within a self-organizing kinematic manifold [9]. At this point, the use of the LET (Lyapunov-Entropy-Topology) framework is necessary, where, by calculating the largest Lyapunov exponent, it effectively maps the stability corridors alongside the chaotic shifts [9]. While using Shannon entropy, we measure the structural disorder that hides inside noisy, complex movement data [21]. The adoption of this information-theoretic perspective lays the foundations of our analysis and allows us to objectively define the cross-efficiency

weights, which means that our conclusions remain locked to what the raw numbers actually show [22].

Observing carefully, it is determined that the muscles and joints operate as a decentralized network, where they continuously try to balance their entropic cost. In computational terms, the internal balancing act of the body looks very much like a maximum-entropy multi-agent dynamic state [23]. The motor units must communicate ceaselessly to maintain postural equilibrium. This kind of biological teamwork directly mirrors ad hoc coordination models that operate with best-response rules [24]. Many researchers, in their attempt to map these complex interactions, rely heavily on physics-guided deep learning [25] or multi-agent credit assignment [26]. The problem, of course, with these approaches is that they completely lose transparency and become computational black boxes.

It is known that biological wear shares basic characteristics with neuromorphic dynamics [27]. However, the evaluation of a factory environment through these massive mathematical models is infeasible. Through the LET framework, this process is bypassed to extract fundamental topological features, where chaotic kinematic entropy is quickly and transparently converted into a reliable diagnostic metric. A basic regression model might offer a decent starting point, which, however, dissolves the moment you introduce the high-dimensional, chaotic reality of the actual biomechanical strain [28].

1.4. Explainable AI and Kinesthetic Intervention

Industry 5.0 sets human-centric intelligence as its main pillar. For this reason, Explainable Artificial Intelligence (XAI) constitutes a significant factor in order to untangle the massive data patterns and transform them into forms that the user can read and trust [29]. In the extensive field of biomechanics, XAI connects algorithmic guesses directly to measurable physical traits, essentially guaranteeing that every diagnostic warning aligns with the actual clinical truth [30]. Using previous organizational indices as a basis, the strict control of the actual kinematic stability of the body during work is feasible [31].

Garments like the Funabot Suit are based on McKibben artificial muscles to provide mild and natural kinesthetic feedback, preventing any physical damage [32]. The alteration of ergonomics into a live control loop of endogenous state variables is achieved through the Dynamic Integrity Governor (DIG), as schematically illustrated in the operational closed-loop architecture of Figure 1. In this way, the muscles of a worker are kept safe even in the case that their movements become extremely unpredictable [8]. In the present study, non-linear metrics are merged with strict statistical analysis and pinpoint the exact moment when the movement collapses into chaotic instability. The final goal is to create an unshakeable scientific foundation that will limit or even eliminate musculoskeletal injuries in the work environment.

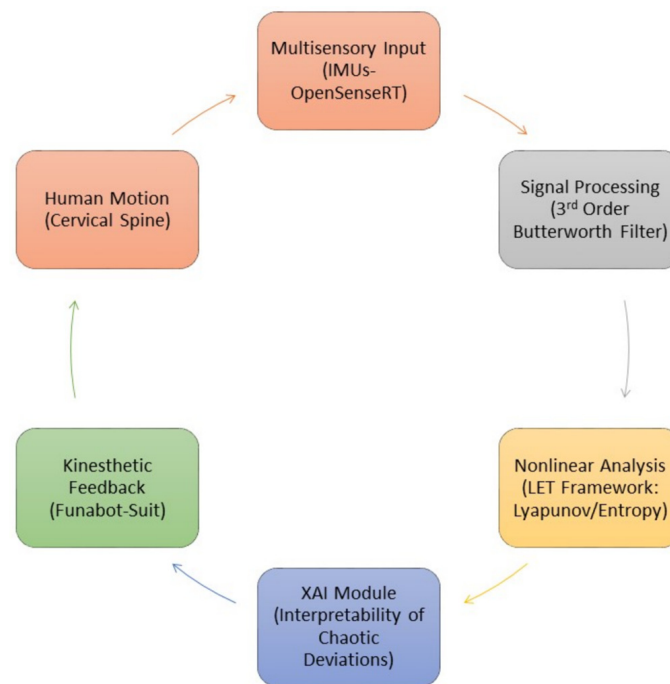


Figure 1. Operational closed-loop architecture for ergonomic governance. The framework integrates real-time cervical kinematics (OpenSenseRT) with nonlinear LET estimation and XAI-mediated diagnostics to modulate corrective kinesthetic feedback via the Funabot-Suit.

2. Methodology

2.1. Scope and Design Framework

For the validation of the LET (Lyapunov, Entropy, Topology) framework, the transition from traditional Digital Human Modeling (DHM) to a Human-Centric Digital Twin (HDT) architecture is necessary [9]. For this study, we have selected cervical kinematics as the primary focal point because this region exhibits high stochastic complexity and is prevalent in work-related musculoskeletal injuries (MSI) that arise from non-linear fatigue accumulation [2,15].

2.2. Participants and Proof-of-Concept (PoC) Justification

Given the Proof-of-Concept (PoC) nature of this preliminary validation, a single-subject experimental design ($N = 1$, healthy male, age: 32 years) was employed. Inclusion criteria for the test subject required the absence of prior cervical musculoskeletal disorders, neurological deficits, or recent surgeries. While this single-case approach inherently restricts population-level generalizability, it is methodologically rigorous and entirely sufficient to establish the computational viability, sensor integration, and phase-space behavior of the LET framework. Extensive empirical validation on a statistically powered, anthropometrically diverse cohort is reserved for future large-scale human-subject trials.

2.3. Hardware Instrumentation and Anatomical Reference

To collect data in real time, the OpenSenseRT system was utilized. The sensors were placed could record the cervical biomechanics with the highest fidelity. The main computational unit consists of an Arduino-compatible microcontroller (Arduino Uno R3, Arduino LLC, Somerville, MA, USA) interfaced with a 6-axis Inertial Measurement Unit (IMU, MPU6050, InvenSense Inc., San Jose, CA, USA), as well as a flexible bend sensor (SparkFun Electronics, Niwot, CO, USA) [33] (for detailed electronic schematics and pinout configurations, see Supplementary Figure S1). For the monitoring and recording of the

cervical flexion angle a flexible sensor was used, while the IMU recorded the continuous 6-DOF kinematic data to ensure the topological analysis.

Wanting to ensure absolute topological accuracy as well as the mitigation of initial errors that could arise due to sensor-to-segment misalignment, the IMU is housed in a 3D-printed Polylactic Acid (PLA, Prusa Research a.s., Prague, Czech Republic) casing. Two spirit levels have been integrated into the casing, one on the vertical and one on the horizontal axis, as depicted in Figure 2. More specifically, one spirit level has been positioned horizontally above the sensor, and the second is aligned sagittally to ensure the precise orientation of the horizontal plane, aligning the tragus of the ear with the infraorbital margin.

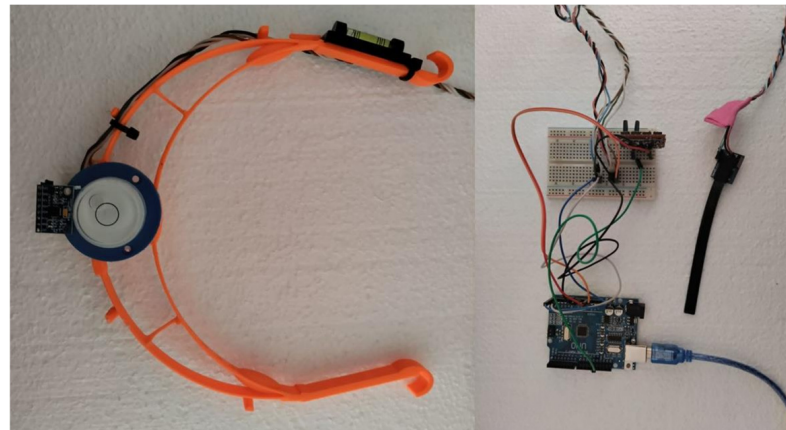


Figure 2. The hardware configuration of the wearable system, detailing the Arduino microcontroller, the flexible bend sensor, and the IMU enclosed within the custom 3D-printed PLA housing equipped with dual orthogonal spirit levels for anatomical calibration.

The wearable sensors are secured to the participant using non-invasive, skin-adhesive kinesiology tape to ensure kinematic fidelity. A two-node configuration is applied:

- **Fixed Segment:** The sensor is positioned on the spinous process of the 7th cervical vertebra (C7) to function as the fixed anatomical reference for the relative angular calculations [19].
- **Moving Segment:** The sensor is positioned on the anterior part of the cranium, secured to the casing, to carry out the recording of the cephalic trajectories in relation to the trunk.

The continuous relative trajectories are important for the study as they constitute the empirical basis for the reconstruction of the system's dynamic phase space. As conceptually depicted in Figure 3, this mathematical representation is critical for mapping the biomechanical shift from syntropic stability, which is distinguished by limit cycles under low-strain conditions, to chaotic, entropic instability, which is expressed as strange attractors under high-strain conditions.

2.4. Calibration and Stochastic Baseline

Initially, and prior to any movement, a 10 s static calibration phase is conducted in a Neutral Posture (0°) and full balance of the two spirit levels to carry out the appropriate estimation of the gyroscope bias and the determination of the sensor's stochastic limit [33]. The average of the data in this state aims to guarantee that the subsequent non-linear estimation of the Maximum Lyapunov Exponent (LyE) is based on a reference state with attenuated noise [34,35].

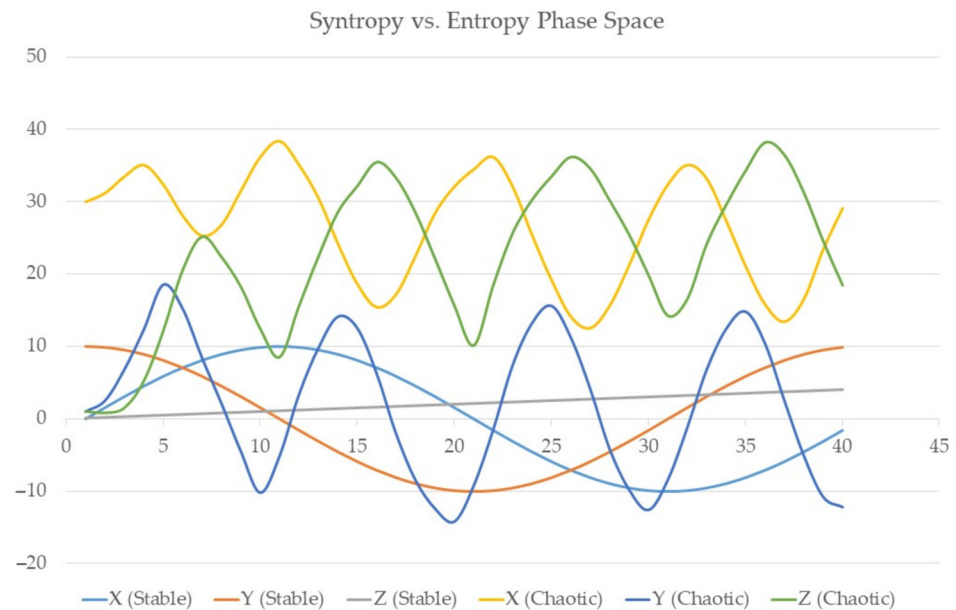


Figure 3. Conceptual phase-space trajectories of cervical motion under different ergonomic regimes. The blue trajectory (Syntropy) represents ordered stability through a limit cycle, characteristic of the low-strain 0–30° range. The red trajectory (Entropy) illustrates the emergence of chaotic instability and strange attractor behavior in high-strain regimes (45°+), where the Largest Lyapunov Exponent (LyE) quantifies the loss of local dynamic stability.

2.5. Motion Protocol and Biomechanical Regimes

The participant executes a structured sequence of sagittal flexion/extension movements. The angular increments represent discrete states of biomechanical loading derived from Hansraj [36]:

1. Neutral (0°): Reference state that undergoes minimal fatigue due to the support of the head (~5 kg) with minimal entropy production.
2. Ergonomic Threshold (30°): It is subjected to a four-fold increase in the load (~18 kg) and transitions into the levels of ergonomic risk [15].
3. High-Strain Regime (45°+): At these levels, it reaches an active load of ~22.2 kg; thus, the conditions are set to appropriately observe the moment when local stability collapses and transitions toward chaotic instability, as quantified by the LyE.

During the variation in the lever arm, we observe the non-linear increase in the active gravitational load that acts upon the cervical spine. The active force F_{eff} is expressed as a function of the flexion angle θ (Figure 4):

$$F_{eff} = W_{head} \cdot (1 + k \cdot \sin \theta) \quad (1)$$

where W_{head} is the actual weight of the head (~5 kg) and k is a scaling constant derived from the Hansraj model [36] to account for the biomechanical leverage escalation reaching ~22.2 kg at 45°.

2.6. Hysteresis and Fatigue-Recovery Protocol

In the experimental procedure, a fatigue recovery protocol has been integrated so that the observation of the transfer from syntropic stability to chaotic instability is feasible. The goal of the study is to allow the evaluation of the localized cervical hysteresis, which is defined as the temporal delay in the restoration of local dynamic stability after prolonged isometric strain. The protocol is structured into discrete temporal nodes:

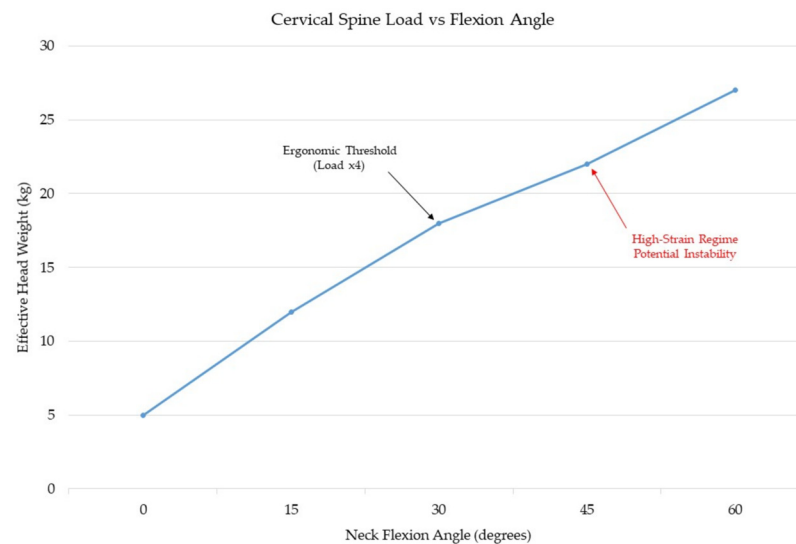


Figure 4. Non-linear escalation of effective head weight acting on the cervical spine as a function of neck flexion angle. The plot identifies the ergonomic threshold at 30° (representing a four-fold load increase from the neutral position) and the transition into a high-strain regime beyond 45° , where potential kinematic instability and increased musculoskeletal risk occur (based on the Hansraj biomechanical model [36]).

1. **T_0 (Baseline/Syntropy-Kinematic Calibration):** The subject sits on a typical office chair with the lumbar spine supported. Following the static calibration of 10 s at the reference point for the determination of the sensor's stochastic limit, the subject executes continuous, cyclic sagittal flexion-extension movements ($0^\circ \rightarrow 45^\circ \rightarrow 0^\circ$) for exactly 120 s. The kinematic velocity is strictly regulated via an auditory metronome set at 60 beats per minute (bpm), dictating a total cycle duration of 4 s (yielding 30 continuous cycles). In this phase, the reference state is recorded, in which there is no fatigue, for the calculation of the initial Lyapunov Exponent ($\text{LyE} \leq 0$) (Figure 5).
2. **T_1 (Isometric Fatigue Induction-Static Load Accumulation):** In this phase, the subject is loaded biomechanically, prolonged for 15 min, simulating occupational tasks. A visual target is placed near the thighs of the subject, enforcing a static 45° cervical flexion. According to the biomechanical model of Hansraj [36], in this body posture, the load exerted on the lower cervical spine due to the increased lever arm of the mass of the head corresponds to ~ 22.2 kg. It is important to note that no external weights were used; the fatigue was induced exclusively through the isometric maintenance of this high-strain posture (Figure 6).
3. **T_2 (Peak Entropy-Chaotic Transition):** For the recording of the maximum dynamic disruption, the subject, after completing the 10 s static calibration, immediately repeats the dynamic motion protocol. The subject executes the flexion-extension cycles with the rhythm of the metronome for another 120 s, identically to phase T_0 . The localized muscular fatigue is manifested as stochastic, high-frequency micro-deviations from the main axis of motion ($\text{LyE} > 0$).
4. **T_3 (Hysteresis and Recovery Dynamics):** After phase T_2 , the subject returns to the neutral posture and rests actively on the back of the chair to fully unload the cervical and thoracic region of the muscular system. At the end of the passive recovery of 180 s (T_3), the 120 s dynamic protocol is repeated for a third and final time. This sequential recording identifies the decay of the LyE and quantitatively maps the biomechanical hysteresis.



Figure 5. The experimental setup demonstrating the anatomical placement of the dual-node sensor array on the cranial vertex and the C7-T1 region. The subject maintains a neutral, fully supported seated posture (0° cervical flexion) during the T_0 baseline calibration phase. This position establishes the initial syntropic stability, supporting the actual anatomical head weight of ~ 5 kg prior to workload induction. (Note: Facial features have been obscured to maintain subject anonymity in accordance with ethical guidelines.)

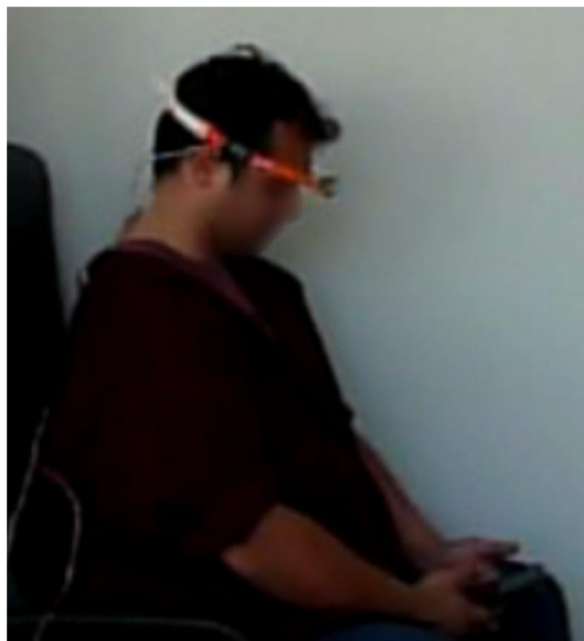


Figure 6. The experimental setup demonstrating the anatomical placement of the sensor array on the C7-T1 region. The subject maintains a static 45° cervical flexion to induce localized isometric fatigue, generating an internal biomechanical effective load of ~ 22.2 kg without external weights. (Note: Facial features have been obscured to maintain subject anonymity in accordance with ethical guidelines.)

2.7. Signal Processing and Phase-Space Reconstruction

The collected raw kinematic time-series data were processed to isolate the actual cervical motion from external noise. The relative angular displacement $\theta(t)$ and angular velocity $\omega(t)$ were calculated by subtracting the vector of the C7 base segment from the cranial moving segment. To mitigate high-frequency sensor noise and electromechanical artifacts, the raw signals were passed through a zero-phase 3rd-order low-pass Butterworth

filter with a strictly defined cutoff frequency of 2.5 Hz. Based on foundational biomechanical signal processing [37], the energy of voluntary human kinematics is heavily concentrated below 3.0 Hz. Given that the metronome-paced movement protocol dictated a 4 s cycle duration (0.25 Hz fundamental frequency), the 2.5 Hz cutoff explicitly preserves up to the 10th harmonic of the motion. This ensures the capture of the complete physiological bandwidth without distortion. Furthermore, operating at a 6.67 Hz data acquisition rate, this filter configuration strictly adheres to the 3.33 Hz Nyquist-Shannon limit, inherently functioning as a robust anti-aliasing mechanism.

During the reconstruction of the phase space, identical successive sensor readings pose a risk for algorithmic singularities. To prevent this, a uniform micro-stochastic Gaussian dither $N(0, 10^{-5})$ was injected into the signal [38,39]. A preliminary sensitivity analysis confirmed that this noise amplitude is several orders of magnitude below the macroscopic kinematic variance, ensuring continuous differentiability of the trajectory without structurally biasing the strange attractors or altering the macro-kinematic properties.

Finally, for the evaluation of the dynamic stability, the univariate kinematic time-series have been embedded into a multidimensional phase space making use of Takens' delay coordinate embedding theorem. The state vector at time t is defined as

$$X(t) = [\theta(t), \theta(t + \tau), \dots, \theta(t + (m - 1)\tau)] \quad (2)$$

where τ represents the time delay and m is the embedding dimension. The optimal time delay is determined using the Average Mutual Information (AMI) criterion, while the embedding dimension is estimated via the False Nearest Neighbors (FNN) algorithm [40].

This geometric method identifies points that appear as neighbors in a lower-dimensional space solely due to projection artifacts rather than true dynamic proximity. A nearest neighbor X_j to a given point X_i in dimension m is computationally classified as a false neighbor in dimension $m + 1$ if the normalized distance variation exceeds a heuristic threshold R_{tol} :

$$R_i = \frac{\|X_{i,m+1} - X_{j,m+1}\|}{\|X_{i,m} - X_{j,m}\|} > R_{tol} \quad (3)$$

By iteratively calculating this ratio across the dataset, the minimum embedding dimension was robustly identified at the point where the percentage of false nearest neighbors approached zero, mathematically guaranteeing a topologically unfolded and singularity-free attractor prior to the extraction of the Lyapunov Exponents.

2.8. Non-Linear Feature Extraction (LET Metrics)

- **Largest Lyapunov Exponent (LyE):** The LyE was extracted using the Rosenstein algorithm, capturing the exponential divergence of the initially nearest neighbors in the reconstructed phase space [41]. In the event that the LyE approaches zero or negative values, stable, syntropic behavior is indicated, whereas in the event that it approaches a positive value, it functions as a mathematical biomarker of chaotic instability. It is important to point out that the scalar LyE magnitudes reported in the present study (6.98–8.04) represent the unnormalized, cumulative logarithmic divergence across the embedding window, quantified in bits per discrete sample, utilizing base-2 logarithms. In contrast to studies that normalize the LyE based on continuous time, the present metric is sample-based and prevents scaling artifacts caused by division in extremely short-duration and low-frequency isometric tasks. Consequently, these values serve as highly sensitive, relative intra-subject metrics for the exclusive evaluation of the transition rate from syntropic stability to chaotic entropic states.

- **Shannon Entropy (H):** The reconstructed phase space was partitioned into a discrete grid of equiprobable microstates, utilizing a uniform multidimensional coarse-graining technique to achieve the evaluation of the structural disorder of the motion. To enable the assurance of mathematical reproducibility and to prevent arbitrary entropy scaling, the number of discrete bins is denoted as k and was determined empirically using Sturges' rule:

$$k = 1 + \log_2(n) \quad (4)$$

where n is the total number of recorded kinematic data points. The probability p_i that the system occupies the i -th state is used to calculate the information-theoretic entropy:

$$H = -\sum_i p_i \log_2(p_i) \quad (5)$$

The grid boundaries were kept globally constant across every experimental phase (T0 to T3) in accordance with the absolute maximum and minimum kinematic amplitudes of the entire dataset. This uniform binning scheme with fixed boundaries ensures that the reported entropy values project the relative changes in biomechanical structural disorder. An increase in the variable H makes clear the loss of motor control precision, the proliferation of unpredictable micro-tremors, and the transition toward entropic structural collapse.

3. Results

3.1. Baseline Kinematics and Syntropic Stability

During the state where the neck is at rest (T_0 _Baseline), its trajectories in the phase space exhibited an extremely organized topological structure. The continuous cyclic movements produced a well-defined limit cycle attractor. According to the theoretical expectation of local dynamic stability, termed here as *syntropy* (the state of organized, negative entropic flow), the calculated Maximum Lyapunov Exponent (LyE) was found to be 6.9839 along the main flexion/extension axis (Pitch). The structural disorder that was quantified by the Shannon Entropy remained relatively limited at 4.9875 bits for the main axis and at 4.6315 bits for the lateral axis (Roll), indicating a high degree of kinematic predictability and coordinated motor control prior to the introduction of the workload.

3.2. Fatigue-Induced Chaotic Transitions and Compensatory Stiffening

The dynamics of the system shifted profoundly after the fatigue of the neck and its forward extension for a prolonged active load of ~22.2 kg (T_2 _Fatigue). A distinct dispersion in the phase space trajectories was perceived, which is characterized by high-frequency micro-deviations from the main axis of motion. The LyE increased significantly to 8.0362, thereby confirming the onset of chaotic instability through mathematical means. This escalation is indicative of neuromuscular uncoupling, which is defined as the ability of the central nervous system to execute precise micro-corrections. As local muscular fatigue accumulates, this results in a higher orbital divergence in the reconstructed phase space.

The analysis of the information-theoretic Shannon Entropy also revealed an extremely divergent, axis-specific entropic behavior, directly validating the theoretical assumptions of the LET framework. On the primary axis of motion (Pitch), an augmentation in entropy from the baseline value to 5.0143 bits was observed, thereby inferring the stochastic nature of fatigue accumulation. This phenomenon is characterized by micro-vibrations and a loss of rhythmic consistency. In particular, the biological system appears to encounter difficulties in sustaining a deterministic trajectory along the primary execution axis. Conversely, the lateral axis (Roll) demonstrated a consistent decline in entropy, reaching 4.1674 bits. This

inverse phenomenon is indicative of a quantitative manifestation of the phenomenon known as “Compensatory Stiffening”. As the physiological strain increases under the load of ~22.2 kg, the human body instinctively applies a mechanical locking mechanism to the secondary degrees of freedom (lateral bending) to prevent the total collapse of the posture. The system has been configured such that the lateral axis is rendered rigid, thus, artificially reducing the lateral kinematic entropy. This is in order to compensate for the chaotic divergence observed in the main axis.

3.3. Hysteresis and Dynamic Recovery Latency

Upon entering the recovery phase ($T_{3_Recovery}$), the temporal tracking of the non-linear metrics mapped the hysteresis curve of the cervical system. After the short-term rest interval, the LyE decreased to 7.0086. While this indicates a substantial restoration of dynamic stability and a return toward syntropic flow, the failure of full reversion to the exact baseline value (6.9839) makes clear the presence of a mild hysteresis effect. The motor control system retains a “kinematic memory” of the fatigue, indicating a latency in structural recovery.

The entropy metrics prove the lack of complete biomechanical recovery. The entropy of the main axis continued to peak at 5.0698 bits, while the entropy of the lateral axis was further minimized to 3.7225 bits. The prolonged compensatory stiffening in the secondary axis, combined with the lingering stochasticity in the main axis, mathematically proves that short-term rest periods are insufficient for the complete dissipation of structural disorder and full topological recovery.

4. Discussion

4.1. Decoding Neuromuscular Uncoupling via Kinematic Chaos

The results of the experiment bring forth a fundamental shift in the way in the understanding of ergonomic fatigue, because it is not a simple local drop of muscle energy. The resulting data reveal a systemic topological disruption. During the examination of the Maximum Lyapunov Exponent (LyE), a sharp increase is observed from the baseline state (6.9839) to the fatigue state (8.0362). This jump functions as a mathematical footprint of what is termed Neuromuscular Uncoupling. During the resting phase, the central nervous system controls movement efficiently, maintaining the cervical trajectories in a tight limit cycle. However, from the moment that the active load of 22.2 kg brings about the corresponding loading, the system loses its ability to make micro-corrections with the necessary precision, with the result that the trajectories diverge exponentially.

The hysteresis analysis also highlights a significant delay in the recovery of the body. Even after a rest interval of 180 s, the LyE decreased only to 7.0086, without ever returning fully to the baseline value, revealing that the short-term rest breaks, which constitute a common practice in modern workplaces, are not sufficient for the restoration of biomechanical syntropy. The motor system maintains in reality a kinematic memory of the strain.

4.2. The Compensatory Stiffening Phenomenon: A Paradigm Shift from Linear Ergonomics

Perhaps the most interesting diagnostic insight from our LET framework is the axis-specific behavior observed during the phase of long fatigue. Traditional tools like RULA or OWAS treat the human body as a static linkage system. If someone bends their neck at 45 degrees, a conventional RULA assessment simply assigns a static high-risk score, completely ignoring the internal mechanical strain that evolves over time. Applying Shannon Entropy to the continuous kinematic flows, the hidden dynamics of “Compensatory Stiffening” were revealed. As the subject became more tired, the main axis of motion (Pitch) became increasingly disordered, peaking at 5.0698 bits, reflecting the failure of

the main extensor muscles and the production of micro-vibrations. Unexpectedly, the entropy on the secondary lateral axis (Roll) decreased significantly to 3.7225 bits. This reverse behavior proves that as the main axis collapses into chaos, the body tries to survive by artificially locking its secondary movements, with the result of setting the lateral axis becoming rigid to prevent a total fall of the posture. This dynamic phenomenon cannot be captured by conventional, linear Digital Human Modeling (DHM) tools and kinematic simulation frameworks.

4.3. Closing the Loop: XAI, Digital Twins, and Proactive Kinesthetic Intervention

Bioergonomics pursues the alteration of musculoskeletal monitoring from a passive state to an active closed-loop governance. The extraction of the LET metrics (LyE and Shannon Entropy) provides the mathematical foundation for a real Human-Centric Digital Twin (HDT). These continuous nonlinear variables constitute the interpretable features required for Explainable Artificial Intelligence (XAI) architectures, in order to monitor the conditions in an industrial environment. Safety algorithms can explicitly attribute the impending risk to measurable physical phenomena, such as “kinematic divergence” or “compensatory stiffening”, without relying on opaque deep learning decisions.

Thanks to this diagnostic ability, there is the possibility of immediate updating of the proactive physical interventions in real time. It is speculated that the systems will have the ability to react proactively to the onset of chaos if the ergonomic load is treated as an endogenous state variable. Consider the case of the detection of a critical entropic threshold (e.g., an abnormal decrease in the lateral entropy combined with a sharp increase in the stochasticity of the main axis). In a scenario like the above, bio-inspired assistive devices like the Funabot Suit have the ability to dynamically modulate the feedback via McKibben artificial muscles. The creation of a cyber-physical control loop has been proven that it can offer immediate kinesthetic support to the user, thereby restoring the syntropic organization before the onset of the cumulative structural damage occurs.

5. Conclusions and Future Work

This study established a robust and nonlinear methodological framework for the quantification of ergonomic strain, demonstrating a necessary paradigm shift from static, linear assessments toward dynamic topological analysis. Exploiting the time-delay phase-space reconstruction and information-theoretic metrics, the proposed LET framework captures the complex biomechanical realities of musculoskeletal fatigue with particular success. In the study, the phenomenon of neuromuscular uncoupling is mathematically validated through the escalation of the Largest Lyapunov Exponent, while “compensatory stiffening” is uniquely identified through the axis-specific divergence of Shannon entropy. The integration of zero-phase Butterworth filtering and the addition of micro-stochastic Gauss noise (Gaussian dither) ensures the mathematical resilience of these estimators against common field-data artifacts, consolidating the diagnostic validity of the framework.

The current experimental design provides a high-fidelity proof-of-concept for the LET mathematical architecture; nevertheless, future work must focus on extensive empirical validation. The next stages of this research will include the application of the OpenSenseRT protocol to a statistically significant and anthropometrically diverse group of human subjects. A larger-scale experimental validation will be critical for the establishment of the statistical reproducibility of the observed entropic thresholds, the evaluation of inter-subject kinematic variability and, consequently, the generalization of the Syntropic Bioergonomics paradigm across various industrial and occupational populations.

Furthermore, to address the constraints of strictly controlled laboratory environments, future iterations of the LET framework must expand beyond simplified sagittal loading

to accommodate complex, multi-axis movements and torsional mechanical stressors typical of dynamic industrial settings. In addition, subsequent experiments will encompass empirical evaluations of the real-time closed-loop feedback mechanisms, particularly the integration of the XAI diagnostic module with assistive hardware, such as the Funabot Suit, to methodically verify operational latency and in vivo injury prevention efficacy.

Supplementary Materials: The following supporting information are available online: <https://doi.org/10.5281/zenodo.22913989>, Supplementary Figure S1: Electronic Schematic of the Custom Sensory Node. This wiring diagram details the hardware integration of the Arduino-compatible microcontroller with the MPU6050 (6-DOF IMU) via the I2C protocol, alongside the analog interface of the flexible bend sensor utilized for real-time kinematic data acquisition. Supplementary Video S1: Baseline Kinematic Protocol and Syntropic Stability (T_0). This video demonstrates the initial experimental phase, including the 10 s static calibration in the neutral posture (0°). It subsequently captures the participant executing the continuous, metronome-paced (60 bpm) sagittal flexion-extension movements ($0^\circ \rightarrow 45^\circ \rightarrow 0^\circ$), visually representing the rested, syntropic biomechanical state (stable limit cycle). Supplementary Video S2: Isometric Fatigue Induction and Chaotic Transition (T_1 & T_2). This video illustrates the application of the sustained ~ 22.2 kg effective load. It shows the participant maintaining the unassisted static 45° cervical flexion. The footage captures the visible onset of localized muscular fatigue (micro-tremors) and the immediate transition to the dynamic motion protocol (T_2), demonstrating the fatigue-induced chaotic divergence in the kinematic trajectories.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Written informed consent has been obtained from the participant to publish this paper and any accompanying multimedia files.

Data Availability Statement: The continuous kinematic datasets generated and analyzed during the current study, alongside the custom algorithms developed for the LET framework and the sensor acquisition firmware, are openly accessible via GitHub at the following repository: [<https://github.com/Nikitas-G/syntropic-bioergonomics-data.git>] (accessed on 16 September 2026). Computational implementation and non-linear dynamic analyses were performed in Python (version 3.10) hosted on the Google Colab cloud platform (Google LLC, Mountain View, CA, USA), while microcontroller firmware deployment and sensor streaming were managed through the Arduino Integrated Development Environment (Arduino IDE, version 2.3.2; Arduino LLC, Somerville, MA, USA). The experimental protocol involving human subjects was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics and Deontology Committee (EHDE) of the University of West Attica (UNIWA, protocol code: 46607/07-05-2026).

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Abbreviations

The following abbreviations are used in this manuscript:

LET	Lyapunov-Entropy-Topology
LLE	Largest Lyapunov Exponent
LyE	Lyapunov Exponent (Clinical context)
XAI	Explainable Artificial Intelligence
DIG	Dynamic Integrity Governor
CADI	Chaos-Aware Design Index
IMU	Inertial Measurement Unit
REBA	Rapid Entire Body Assessment
DHM	Digital Human Modeling
HDT	Human-Centric Digital Twin
CNN-LSTM	Convolutional Neural Network-Long Short-Term Memory
PoC	Proof of Concept

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